# CAN PREVENTIVE WEED MANAGEMENT HELP INCREASING HERBICIDE USE EFFICIENCY? EVIDENCE FROM MAIZE FIELDS IN GERMANY

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**Abstract**

Due to the multiple negative environmental effects of the overuse of chemical pesticides, the European Union (EU) aims to reduce pesticide use – including herbicides – by 50%, by 2030. Preventive weed management (PWM), using among others in-version tillage and diverse crop rotations, is considered perhaps the most suitable strategy to reduce on-farm herbicide use. Whether and how these practices relate to herbicide reduction potential and crop yields is, however, not well understood. This paper addresses this gap by investigating the impact of PWM on maize yields and herbicide use. Using field-level data for 530 maize fields in eastern Germany, we apply a directional distance function approach in a data envelopment framework and estimate directional and simultaneous improvement potentials for herbicide use and maize yields. Our preliminary results indicate a similar performance with holistic PWM and without PWM in terms of both yields and herbicide use, whereas a partial implementation of PWM seems to increase herbicide use. We also find herbicide reduction potentials of 36-37% irrespective of the PWM suggesting notable improvement potentials by implementing best practices.

**Keywords:** Herbicide use efficiency, field-level, maize yields, data envelopment analysis

## 1. Introduction

Weed control with synthetic herbicides constitutes the main component of weed management in conventional crop rotations in arable farming (CHAUHAN, 2020). Though, overreliance on herbicide application has multiple negative effects, e.g. the reduction of plant diversity (GUERRA et al., 2022), damaging aquatic and soil organisms (OJEMAYE et al., 2020) and the expansion of herbicide resistant weeds (DAVIS and FRISVOLD, 2017). With the Farm-to-Fork strategy, the Commission of the European Union (EU), therefore, aims at reducing pesticide use – including herbicides – by 50%, by 2030 (TRIANTAFYLLIDIS et al., 2023).

Preventive weed management (PWM) is considered key to reducing herbicide input in arable farming (RIEMENS et al., 2022; TRIANTAFYLLIDIS et al., 2023). PWM strategies entail, among others, inversion tillage and wider crop rotations, and can thus be considered as a traditional management system for maize in Germany (BENSCH et al., 2023). Despite comprehensive policy efforts to reduce pesticide use in arable farming (EUROPEAN COMMISSION, 2009), the rate of preventive weed management adoption remains heterogeneous across European farming (TRAON et al., 2018). To increase adoption of PWM, preventive weed control needs to be perceived as beneficial in order to be regarded as profitable alternatives to conventional input-intensive cropping. Hence, the economic benefits of re-establishing PWM need to be clearly demonstrated before farmers adopt and implement such practices. So far, studies have demonstrated the potential of PWM in field experiments and on-farm mainly for cereal crops (ANDERT and ZIESEMER, 2022; ADEUX et al., 2019). However, whether and how these practices relate to herbicide reduction and crop yield remains not well understood.

We aim at closing this gap and investigate the impact of PWM practices on maize yields and herbicide application. We rely on data from 530 maize fields between 2011 and 2014 in eastern Germany with field-specific information on maize yields, herbicide application (Treatment Frequency Index, TFI) and other land management decisions (N and P fertilization, crop rotation, tillage), and soil quality.

We investigate the effects of PWM using two classifications: First, based on the applied tillage, we compare the performance of fields with and without inversion tillage. Second, based on the crop alteration and the host crop principles (ANDERT et al., 2016), we compare the performance of three levels of PWM practices, reflecting different risks of weed infestation. We define the three levels using pre-crop and the applied tillage and differentiate no PWM (PWM0), some PWM (PWM1), and multiple PWM (PWM2). We compare the fields' performance with and without inversion tillage as well as by PWM level using field-specific efficiency measures. We consider improvement potentials relative to the best practice frontier with respect to maize yields and herbicide application while accounting for other farming inputs and soil quality. To model the best practice frontier, we rely on a metafrontier framework. That is, we assess efficiency relative to the group frontier determined by fields using the same PWM practices (group frontier), and relative to a metafrontier determined by all fields in the sample irrespective of the PWM (BATTESE et al., 2004; HAYAMI and RUTTAN, 1970). Empirical estimates are obtained through directional distance functions in a non-parametric data envelopment analysis framework (CHAMBERS et al., 1996; BANKER et al., 1984).

Our results indicate efficiency advantages of fields under inversion tillage compared to fields without inversion tillage, i.e., lower improvement potentials under inversion tillage. Further, we find higher herbicide use efficiency under inversion tillage without sacrificing maize yields where herbicide reduction potentials are partly only available under tillage. Second, comparing different levels of preventive weed management, our results suggest that in comparison to implementing only some PWM practices (PWM1), applying none (PWM0) or multiple (PWM2) practices achieves a higher herbicide efficiency without losses in terms of maize yields. Herbicide reduction potentials are partly available only by implementing none or multiple PWM practices. That is, even when implementing best practices, herbicide reduction potentials under PWM1 are partly only available by switching to PWM0 or PWM2. Therefore, our results suggest that the application of multiple preventive weed management practices can offer reduced herbicide application without yield losses. Rather, our results indicate that applying multiple practices outperforms the selective use of single practices, for which we find negative yield effects but no reduction in herbicide application.

The remainder of the paper is structured as follows: Section 2 explains our data set, Section 3 introduces our empirical framework and our empirical approach. Section 4 shows our results. Section 5 discusses our results and draws preliminary conclusions.

## 2. Data

We rely on a dataset of maize fields in the counties of Teltow-Fläming and Oder-Spree located in the southern part of the Federal State of Brandenburg, Germany. Our observation period spans from 2011 to 2014. The initial sample consists of 575 observations. We eliminate 45 observations with unobserved pre-crop or P fertilization leading to a final sample of 530 observations. We observe 140 fields in 2011 and 2012, 139 in 2013, and 111 in 2014, respectively. The fields are operated by 14 farms, including 2 arable farms (average farm size: 1,350 ha) and 12 mixed farms (1,688 ha).

For each field, we observe (i) field-specific characteristics including the fields' size and soil quality[1], (ii) maize yields, (iii) a farm identifier, and (iv) farmers' land management decisions. Land management decisions include the crop rotation (class of pre-crop), applied tillage, fertilizer application (N use and P use in kg/ha), and field-specific herbicide application. Herbicide application is measured as a treatment frequency index (TFI) calculated as $TFI = \frac{applied\ Herbicides}{max.\ allowed\ Herbicides} \times \frac{treated\ ha}{total\ ha}$. The TFI represents the frequency and intensity of herbicide applications and includes all herbicide applications related exclusively to the maize. The TFI is unbounded and takes values above 1 if herbicides are applied multiple times within the year.

Based on the observed practices, we create two classifications related to potential differences in the risk of weed infestations, as shown in Table 1. First, to test the hypothesis of a non-negative effect of inversion tillage on herbicide use and maize yield, we differentiate fields operated with (214 obs.) and without inversion tillage (316 obs.).

Second, we define three levels of PWM with decreasing risk of weed infestation based on the crop alteration and the host crop principles (ANDERT et al., 2016). The alteration principle concerns the general sowing period (autumn, spring) which is connected to the timing of the last soil movement before sowing. Alteration of the sowing periods between crops decreases the susceptibility of maize crop for adapted weeds. The number of host crops principle states that the higher the number of potential host crops present as pre-crop, the higher is the susceptibility for weeds. This leads to three groups of PWM with decreasing risk of weed infestation: PWM0 (112 obs.) uses no inversion tillage and self-rotations of maize or summer crops as pre-crops; i.e., no preventive weed management measures are applied. PWM1 (220 obs.) consists of fields where some preventive measures are applied, i.e., non-inversion tillage and winter crops as pre-crop, or maize self-rotations with inversion tillage. PWM2 (198 obs.) uses preventive weed management measures with respect to both pre-crop and tillage by applying inversion tillage and no maize self-rotation.

[1] [1] The German soil quality index captures the natural yield capacity of arable farmland. The index considers soil structure, terrain, climatic conditions, water availability, and other natural conditions (Schmitz and Müller, 2020)

**Table 1: Classification by risks of weed infestation (number of observations)**

| **Pre-crop** | **Inversion tillage = Yes** | **Inversion tillage = No** | |
|---|---|---|---|
| Maize | PWM 1 (16) | PWM 0 (78) | *94* |
| Summer crop | PWM 2 (26) | PWM 0 (34) | *60* |
| Winter crop | PWM 2 (172) | PWM 1 (204) | *376* |
| | *214* | *316* | |

Descriptive statistics for the different classifications and corresponding sample sizes by year are shown in Table 2. The classification by inversion tillage (columns 1 and 2) shows on average higher soil quality, higher yields and lower herbicide use (except for 2014) for the non-inversion group. All considered variables are, however, overlapping. The classification by PWM levels (columns 3 to 5) suggests that some PWM measures (PWM1) are applied on fields with higher soil quality, whereas fields with multiple PWM practices (PWM2) show the lowest soil quality rating on average. We note particularly low N and P fertilization on PWM0 fields in 2012, whereas fertilizer quantities are somewhat similar across all groups in the other years.

**Table 2:** Descriptive statistics by tillage and PWM classification and by year

| | | By tillage | | | | | | By PWM group | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Inversion till. | | | Non-Inversion till | | | PWM0 | | | PWM1 | | | PWM0 | | |
| Year | Var. | Obs | Med. | SD | Obs | Med. | SD | Obs | Med. | SD | Obs | Med. | SD | Obs | Med. | SD |
| 2011 | N | 52 | 188.25 | 62.99 | 88 | 174.56 | 154.55 | 22 | 211.0 | 237.8 | 67 | 173.9 | 111.2 | 51 | 188.3 | 60.9 |
| | P | | 47.5 | 25.21 | | 78 | 65.44 | | 74 | 87.9 | | 82 | 55.5 | | 47.5 | 23.3 |
| | SQ | | 24.5 | 5.48 | | 32 | 7.16 | | 30 | 7.2 | | 32 | 7 | | 24 | 5.5 |
| | TFI | | 1.37 | 0.34 | | 1.73 | 0.65 | | 1.6 | 0.4 | | 1.8 | 0.7 | | 1.4 | 0.3 |
| | Yield | | 35.5 | 10.5 | | 37.6 | 6.2 | | 38.7 | 6.1 | | 37.2 | 6.3 | | 35 | 10.5 |
| 2012 | N | 47 | 207 | 60.32 | 93 | 183.4 | 107.82 | 33 | 21.8 | 106.6 | 70 | 207 | 80.5 | 37 | 231.6 | 61.8 |
| | P | | 57 | 39.09 | | 106.0 | 43.66 | | 55.7 | 41.8 | | 109.8 | 40.3 | | 66.6 | 41.9 |
| | SQ | | 24 | 6.42 | | 30 | 6.71 | | 29 | 4.7 | | 30 | 7.3 | | 22 | 6.7 |
| | TFI | | 1.47 | 0.48 | | 1.98 | 0.79 | | 1.8 | 0.5 | | 2 | 0.9 | | 1.5 | 0.5 |
| | Yield | | 36.6 | 7.3 | | 34.0 | 10.5 | | 34.0 | 7.8 | | 34.5 | 11.8 | | 36.6 | 5.7 |
| 2013 | N | 62 | 205.75 | 59.73 | 77 | 168 | 121.59 | 43 | 168.8 | 149.1 | 38 | 168 | 73.4 | 58 | 207 | 60.1 |
| | P | | 57 | 26.59 | | 79.47 | 55.78 | | 78.3 | 62.3 | | 75.4 | 46.2 | | 57 | 26.8 |
| | SQ | | 26 | 4.24 | | 31 | 8.85 | | 30 | 10.1 | | 31 | 7.3 | | 26 | 4.3 |
| | TFI | | 1.25 | 0.57 | | 1.37 | 0.57 | | 1.3 | 0.5 | | 1.5 | 0.6 | | 1.3 | 0.6 |
| | Yield | | 27 | 6.6 | | 33.5 | 5.2 | | 32 | 6 | | 33.5 | 4.1 | | 27.0 | 6.8 |
| 2014 | N | 53 | 201.22 | 57.55 | 58 | 178.5 | 74.48 | 14 | 187.5 | 50.7 | 45 | 178.5 | 79.4 | 52 | 200.9 | 58.1 |
| | P | | 57 | 30.42 | | 98.43 | 41.88 | | 104.2 | 24.6 | | 89.6 | 45.8 | | 56.2 | 30.7 |
| | SQ | | 20 | 4.71 | | 32.5 | 9.85 | | 30.5 | 6.7 | | 34 | 10.3 | | 20 | 4.6 |
| | TFI | | 1.75 | 0.68 | | 1.47 | 0.42 | | 1 | 0.5 | | 1.5 | 0.4 | | 1.8 | 0.7 |
| | Yield | | 36.1 | 9.3 | | 36.9 | 7.9 | | 33.8 | 6.1 | | 39.0 | 7.6 | | 36.0 | 9.1 |

## 3. Methods

### 3.1 The metafrontier framework

To assess field-specific efficiency with respect to maize yields and herbicide application, we rely on a metafrontier framework (BATTESE et al., 2004; HAYAMI and RUTTAN, 1970). That is, for each field, we assess its improvement potential both relative to a best-practice frontier using the same land management practices (group frontier) and relative to the overall best-practice frontier, irrespective of the land management practices (metafrontier).

We consider a maize production technology that transforms inputs $x$ ($x \in R^m$), including herbicides, into yields $y$ ($y \in R^n$). We denote a technology set containing all feasible combinations of inputs and outputs by $\Psi$, such that

(1a) $$\Psi = (x, y | y\ can\ be\ produced\ with\ x).$$

The upper boundary of $\Psi$ defines the metafrontier production function containing all combinations providing the maximum maize yield for a given level of input. Deviations from this frontier are deemed as inefficiency and may result from suboptimal land management decisions, e.g., a non-optimal timing of fertilizer or herbicide application.

Different land management practices may, however, lead to different feasible combinations of inputs and outputs. For instance, a lower weed pressure under preventive weed management might allow higher yields for a given level of herbicide application compared to a field without preventive weed management. In this case, the sets of feasible input/output combinations would differ between different land management decisions.

We address this using the classifications by inversion tillage and PWM to define $C$ ($c = 1, \dots, C$) subtechnologies. For each subtechnology, we denote the set containing all feasible combinations of inputs and outputs as $\Psi^c$ such that

(1b) $$\Psi^{c} = (x, y | y\ can\ be\ produced\ with\ x\ under\ c).$$

The upper boundary of $\Psi^c$ denotes the best-practice group frontier under $c$, i.e., all combinations providing the maximum maize yield for a given level of input under c. By construction, the group frontiers are enveloped by the metafrontier ($\Psi^c \subseteq \Psi\ \forall c$).

To identify herbicide and yield improvement potentials, we consider the distance of observed input/output levels to the best-practice combinations defined by the metafrontier and the group frontier, respectively. For some observation $i$ using $c$, we indicate the distance to the metafrontier and the group through directional distance functions $\beta_i$ and $\beta_i^c$ (, such that

(2a) $$\beta_i(x_i, \mathrm{y_i} | d) = \sup\{\beta_i \geq 0 \big| \left(x_i - \beta_i d_x, y_i + \beta_i d_y\right) \in \Psi\},$$

(2b) $$\beta_i^c(x_i^c, \mathrm{y_i^c} | d, c) = \sup\{\beta_i \geq 0 \big| \left(x_i^c - \beta_i d_x, y_i^c + \beta_i d_y\right) \in \Psi^{\mathrm{c}}\}.$$

Therein, $\beta_i$ and $\beta_i^c$ are distance functions that indicate the maximum inputs reduction in the direction $d_x$ ($d_x \in R^m$) and the maximum output expansion in the direction $d_y$ ($d_y \in R^n$) while staying in the respective technology sets $\Psi$ and $\Psi^c$ (CHAMBERS et al., 1996).

Therefore, if subtechnology $c$ coincides with the metatechnology, then $\beta_i = \beta_i^c$. If the technologies are not identical, i.e., the metatechnology allows a higher output/input ratio, $\beta_i > \beta_i^c$. The ratio of the distance functions, $\theta_i = \beta_i^c / \beta_i \leq 1$, describes the share of improvement potential that is available using $c$, whereas $1 - \beta_i^c / \beta_i$ describes a potential improvement in terms of inputs and outputs that is only available through switching from subtechnology $c$ to the technology shaping the metafrontier.

Figure 1 illustrates the metafrontier framework for a field (circle) using subtechnology $C1$ and a second field (triangle) using subtechnology $C2$. The common metafrontier $\Psi$ provides the best available input/output combinations, where technology $\Psi^{C1}$ partly coincides with the metafrontier. Arrows with solid (dotted) lines indicate the distance functions $\beta_i^c$ ($\beta_i$) relative to the corresponding subtechnologies (metafrontier); horizontal improvements correspond to pure input reductions ($d_x > 0 \wedge d_y = 0$), whereas vertical improvements relate to an output expansion ($d_x = 0 \wedge d_y > 0$). Joint input-output improvements ($d_x > 0 \wedge d_y > 0$) are omitted for clarity. In this example, output improvement potentials for observation 1 are identical when measured against metafrontier and subtechnology, leading to a metatechnology ratio equal to one. In contrast, input reduction potentials for observation 2 indicate notably higher input savings potentials against the metafrontier compared to the group frontier. These input savings potentials are only available through a switch to a technology defining the metatechnology, which would be indicated by a metatechnology ratio smaller than one.

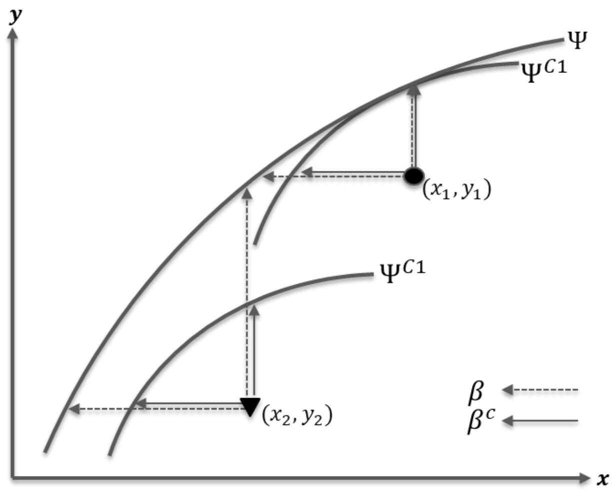


Figure 1: Exemplary illustration of the metafrontier framework (Source: Own illustration)

### 3.2 Group frontier and metafrontier estimations

To simultaneously estimate the best practice frontiers and the directional distance functions, we rely on data envelopment analysis (DEA, BANKER et al., 1984). DEA is a non-parametric linear programming technique that estimates the best-practice frontier by enveloping the relevant observations with a piecewise linear frontier under assumptions about the shape of the technology. The corresponding distance functions are obtained through contracting and expanding the observed inputs and outputs, respectively, while remaining within the technology set specified by the data and the shape assumptions.

For observation $i$ using c, we solve the following linear programming (LP) problems to obtain estimates $\beta_i$ (eq. 5a) and $\beta_i^c$ (eq. 5b)

(3a) $$\max_{\beta_i,\lambda_1,\ldots,\lambda_K} \beta_i \ s.t.\ x_i - \beta_i d_x \geq \sum_k \lambda_k x_k \,;\ y_i + \beta_i d_y \leq \sum_k \lambda_k y_k \,;\ \sum_k \lambda_k = 1$$

(3b) $$\max_{\beta_i,\lambda_1^c,\ldots,\lambda_K^c} \beta_i^c \ s.t.\ x_i^c - \beta_i^c d_x \geq \sum_k \lambda_k^c x_k^c \,;\ y_i^c + \beta_i^c d_y \leq \sum_k \lambda_k^c y_k^c \,;\ \sum_k \lambda_k^c = 1$$

Both LPs contract inputs $x$ and expand outputs $y$ along the directional vectors $d_x$ and $d_y$ while staying in the (sub)technology determined by observations on the frontier. That is, $\beta_i$ ($\beta_i^c$) is the improvement potentials in terms of the step lengths $d_x, d_y$ to the metafrontier (group frontier). The resulting $\beta$-value equals zero for an observation on the frontier, but is greater than one if improvement potentials are present. Because all group technologies are subsets of the metatechnology, distances measured against the metafrontier exceed distances against the group frontiers ($\beta_i \geq \beta_i^c$) by construction.

The LPs provide weighting factors $\lambda_k$ ($\lambda_k^c$) that determine the point on the frontier against which the distance functions are measured (reference point). We restrict these weights to add up to one ($\sum_k \lambda_k = 1$). This induces convexity of the production set such that the frontier is shaped by observed points without further improvement potentials and their linear combinations. As we impose no further assumptions about the underlying returns-to-scale (RTS), the shape of the frontier is purely data-driven and may simultaneously reflect non-decreasing as well as non-increasing RTS.

### 3.3 Model specification

In our empirical analysis, we consider four inputs: N and P fertilizer use measured in kg/ha, the field's soil quality indicated by the German soil quality index, and the treatment frequency index. On the output side, we use the plot-specific maize yield in dt/ha as the single output.

We estimate separate annual frontiers to mitigate biases from variable agroclimatic conditions. The metafrontier therefore contains all observations from the year of interest. Group frontiers are determined using our classifications by inversion tillage and PWM level.

We consider three different types of improvement potentials: First, we consider a joint improvement of herbicide use and yields. We set the directional vectors to the respective observed sample values and measure simultaneous improvement potentials in herbicide and yield direction using $d_x = (x_{TFI}, 0, 0, 0)$ and $d_y = y$. Second, we consider directional improvement potentials with respect to herbicides. We set $d_x = (x_{TFI}, 0, 0, 0)$ and $d_y = 0$ to obtain herbicide reduction potentials, keeping all other inputs and the yield constant. Third, we set $d_x = 0$ and $d_y = y$ to obtain directional improvement potentials with respect to yields keeping all other inputs constant. Using the observed vector eases interpretation because resulting $\beta$ values indicate improvement potentials in percentage values for each observation.

To evaluate between-group differences, we calculate meta-technology ratios (MTRs) $\theta_i^c = \beta_i^c / \beta_i$. For $\theta_i^c = 1$, observation i's distances to the group and the metafrontier are identical. This indicates that it is feasible to produce on the frontier using technology c. For $\theta_i^c < 1$, metafrontier and group frontier are not identical. Additional improvement potentials are thus available through switching technologies, e.g., from no inversion tillage to inversion tillage.

Our empirical strategy using the non-parametric DEA approach offers us several advantages. Yield improvement potentials and herbicide reduction potentials can be evaluated jointly and separately. The technology is estimated with only mild assumptions on its shape, namely free disposability of inputs and outputs, and convexity. In contrast to parametric approaches, such as stochastic frontier analysis (MEEUSEN and VAN DEN BROECK, 1977; AIGNER et al., 1977), no a priori specification of a functional relationship of inputs and outputs is required. We note, however, that the deterministic nature of the DEA induces a high sensitivity of the frontier and, thus, efficiency estimates against noise and outliers in the data. Data integrity is therefore carefully checked. Frontier estimates obtained through DEA are determined by the most efficient observations in the sample. This can lead to a potential downward-bias of the frontier estimate, resulting in an underestimation of improvement potentials (SIMAR and WILSON, 2000). We address this issue through robustness checks using bootstrapping (SIMAR and

WILSON, 2007). Results reveal nearly identical and highly correlated efficiency scores with and without bootstrapping ($\rho > 0.99$); we therefore refrained from an additional bootstrapping.

## 4. Results

We investigate differences in improvement potentials between fields using (i) inversion and non-inversion tillage, and fields (ii) using none (PWM0), some (PWM1) and multiple (PWM2) preventive weed management practices. We evaluate joint and directional efficiency with respect to yields and TFI. We use Shephard efficiency scores by transforming $\beta$ values to obtain efficiency scores in percentage terms (BOGETOFT and OTTO, 2011). Therefore, an efficiency score of 1 indicates no further improvement potential; a value below 1 indicates the degree to which an observation achieves the frontier in percentage terms.

### 4.1 Inversion tillage and non-inversion tillage

Table 1 summarizes the joint and directional efficiency scores (top) and the corresponding metatechnology ratios by tillage (bottom). For the joint analysis measuring simultaneous yield expansion and TFI reduction, results indicate that fields under inversion tillage are on average more efficient (mean: 0.80) than those under non-inversion tillage (mean: 0.74). Maximum efficiency scores of 1 in both groups indicate that production on the frontier is possible with and without inversion tillage. Metatechnology ratios above 0.9 for more than 75% of the observations likewise suggest that there are some improvement potentials regarding both yields and TFI from switching between inversion and non-inversion tillage.

Directional scores in the TFI direction indicate higher average efficiency scores for the inversion group (mean: 0.64) compared to the non-inversion group (mean: 0.52). The results therefore suggest that the TFI can be reduced by around 36% on average in the inversion group, and by nearly 50% in the non-inversion group, while keeping all other factors constant. In contrast, directional efficiency scores in the yield direction show small differences between the groups (mean: 0.78 for inversion tillage, 0.75 for non-inversion tillage).

Median MTRs close to one indicate that for most fields only minor yield increases and TFI reductions are available through switches between inversion and non-inversion. The MTR distribution indicates, however, some advantages for the non-inversion group at the lower quantiles, suggesting that TFI reduction potentials are available through a switch from non-inversion to inversion on some fields.

**Table 3: Efficiency scores (top) and MTRs (MTR, bottom) by tillage**

| | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| *Joint metafrontier TFI/yield efficiency* | | | | | | |
| Inversion | 0.20 | 0.65 | 0.80 | 0.80 | 0.99 | 1 |
| Non-inversion | 0.10 | 0.59 | 0.74 | 0.74 | 0.93 | 1 |
| *Directional metafrontier efficiency: TFI* | | | | | | |
| Inversion | 0.19 | 0.40 | 0.62 | 0.64 | 0.90 | 1 |
| Non-inversion | 0.10 | 0.26 | 0.47 | 0.52 | 0.75 | 1 |
| *Directional metafrontier efficiency: Yield* | | | | | | |
| Inversion | 0.21 | 0.67 | 0.77 | 0.78 | 0.95 | 1 |
| Non-inversion | 0.22 | 0.68 | 0.77 | 0.75 | 0.92 | 1 |
| *MTR: Joint TFI/yield* | | | | | | |
| Inversion | 0.50 | 0.89 | 1 | 0.93 | 1 | 1 |
| Non-inversion | 0.30 | 0.89 | 1 | 0.92 | 1 | 1 |
| *MTR: TFI* | | | | | | |
| Inversion | 0.28 | 0.88 | 0.98 | 0.90 | 1 | 1 |
| Non-inversion | 0.20 | 0.77 | 0.99 | 0.88 | 1 | 1 |
| *MTR: Yield* | | | | | | |
| Inversion | 0.31 | 0.89 | 1 | 0.95 | 1 | 1 |
| Non-inversion | 0.45 | 0.91 | 1 | 0.95 | 1 | 1 |

Notes: Efficiency scores are based on annual frontiers including all observations. Metatechnology ratios are calculated using group specific-frontiers and the meta frontier

Disentangling the efficiency scores by year shows substantial variation across the observation period (Figure 2). Considering joint yield and TFI improvements, efficiency scores by group and year show higher average efficiency scores and smaller efficiency variances for 2011, 2012, and 2014 for the inversion group, and higher scores for the non-inversion group for 2013. One-sided Kolmogorov-Smirnoff tests comparing the annual scores show p-values close to zero in each case, i.e., statistically significant different distributions of the annual efficiency scores.

Directional efficiency scores show similar patterns, with the inversion group having efficiency advantages in 2011, 2012, and 2014, while the non-inversion group scores higher in 2013.We note substantially higher efficiency scores in the TFI direction for the inversion group in 2011 and 2012, which partly vanish in the remaining two years.

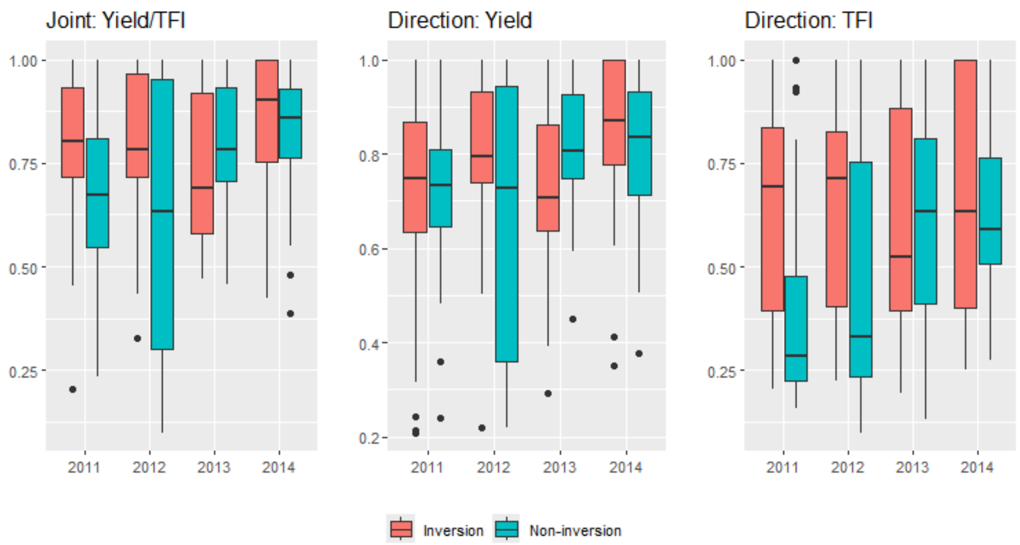


**Figure 2: Radial and directional meta-frontier efficiency scores by year and tillage**

## 4.2 Efficiency by PWM

Table 3 summarizes the joint and directional efficiency scores and the corresponding metatechnology ratios by PWM group. Average joint efficiency scores at similar levels for PWM2 (0.79) and PWM0 (0.78) exceed results for PWM1 (0.70). This suggests that in the PWM1 group, a simultaneous improvement of yields and TFI is possible by around 30% on average, keeping all other factors constant, whereas improvement potentials are at around 21-22% on average for PWM0 and PWM2. Comparing the efficiency score distributions by group using the Kolmogorov-Smirnov test statistic indicates statistically significant differences at the 1% level for PWM0 and PWM2 against PWM1, but no differences between PWM0 and PWM2.

Directional efficiency scores show a similar picture with respect to the TFI. Whereas average efficiency scores with respect to yields are similar across all PWM groups, ranging from 0.74 to 0.79, PWM0 and PWM2 outperform PWM1 in terms of TFI with average efficiency scores of 0.63 (PWM0) and 0.64 (PWM2) compared to 0.47 (PWM1).

For all PWM groups, production on the frontier is possible, as indicated by MTRs equal to one in some observations. The distributions of the MTRs indicate, however, that the frontier is mainly shaped by fields under PWM0 and PWM2. Thus, under PWM1, improvement potentials are to some extent only available through switches to PWM0 or PWM2, respectively.

We also note the wide range of directional efficiency scores under all PWM groups with minima of 0.22 and 0.10, respectively. These inefficiencies are only partly explained by technological differences indicated by the MTRs. Thus, notable potentials to improve yields and reduce herbicide dependence exist through reducing inefficiency, without the need for switching production technologies but through the implementation of best practices.

**Table 4: Efficiency scores (top) and metatechnology ratios (MTR, bottom) by PWM**

| | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| *Joint metafrontier TFI/yield efficiency* | | | | | | |
| PWM 0 | 0.24 | 0.66 | 0.79 | 0.78 | 0.98 | 1 |
| PWM 1 | 0.10 | 0.57 | 0.72 | 0.70 | 0.91 | 1 |
| PWM 2 | 0.20 | 0.65 | 0.80 | 0.79 | 0.99 | 1 |
| *Directional metafrontier efficiency: TFI* | | | | | | |
| PWM 0 | 0.13 | 0.36 | 0.64 | 0.63 | 0.88 | 1 |
| PWM 1 | 0.10 | 0.24 | 0.37 | 0.47 | 0.61 | 1 |
| PWM 2 | 0.19 | 0.40 | 0.63 | 0.64 | 0.93 | 1 |
| *Directional metafrontier efficiency: Yield* | | | | | | |
| PWM 0 | 0.22 | 0.71 | 0.79 | 0.79 | 0.97 | 1 |
| PWM 1 | 0.22 | 0.67 | 0.76 | 0.74 | 0.89 | 1 |
| PWM 2 | 0.21 | 0.67 | 0.78 | 0.78 | 0.93 | 1 |
| *MTR: joint TFI/yield* | | | | | | |
| PWM 0 | 0.38 | 0.79 | 0.97 | 0.88 | 1 | 1 |
| PWM 1 | 0.32 | 0.80 | 0.92 | 0.87 | 1 | 1 |
| PWM 2 | 0.50 | 0.88 | 0.99 | 0.93 | 1 | 1 |
| *MTR: TFI* | | | | | | |
| PWM 0 | 0.20 | 0.68 | 0.96 | 0.82 | 1 | 1 |
| PWM 1 | 0.26 | 0.57 | 0.76 | 0.75 | 1 | 1 |
| PWM 2 | 0.28 | 0.84 | 0.98 | 0.88 | 1 | 1 |
| *MTR: Yield* | | | | | | |
| PWM 0 | 0.65 | 0.80 | 0.96 | 1 | 1 | 1 |
| PWM 1 | 0.50 | 0.90 | 0.96 | 1 | 1 | 1 |
| PWM 2 | 0.32 | 0.88 | 1 | 1 | 1 | 1 |

Notes: Efficiency scores are based on annual frontiers including all observations.
Metatechnology ratios are calculated using group specific-frontiers and the meta frontier

Differentiating efficiency scores by year and PWM group (Figure 3) shows substantial variation across years without pronounced patterns. The joint analysis of yield and TFI improvements (Figure 3, left) shows the highest median efficiency scores for PWM0 and PWM2 in two out of the four years of the observation period. However, PWM1 median efficiency is the lowest only in 2012.

The directional analysis with respect to yields (Figure 3, centre) likewise indicates notable variation of median efficiency scores by group over time without obvious patterns. As for the joint analysis, median efficiency differences are particularly pronounced in 2012, where PWM1 lags behind PWM0 and PWM2. Directional efficiency scores with respect to the TFI (Figure 3, right) indicate the largest heterogeneity between groups and over the observation period. In all years, directional efficiency scores range from below 0.3 to 1 for each group. Median efficiency is lowest for the PWM1 group in all years, whereas the PWM2 group has the highest median efficiency in 2011, 2012, and 2014. The directional analysis thus suggests substantially larger inefficiency in terms of herbicide application compared to the achieved yields.

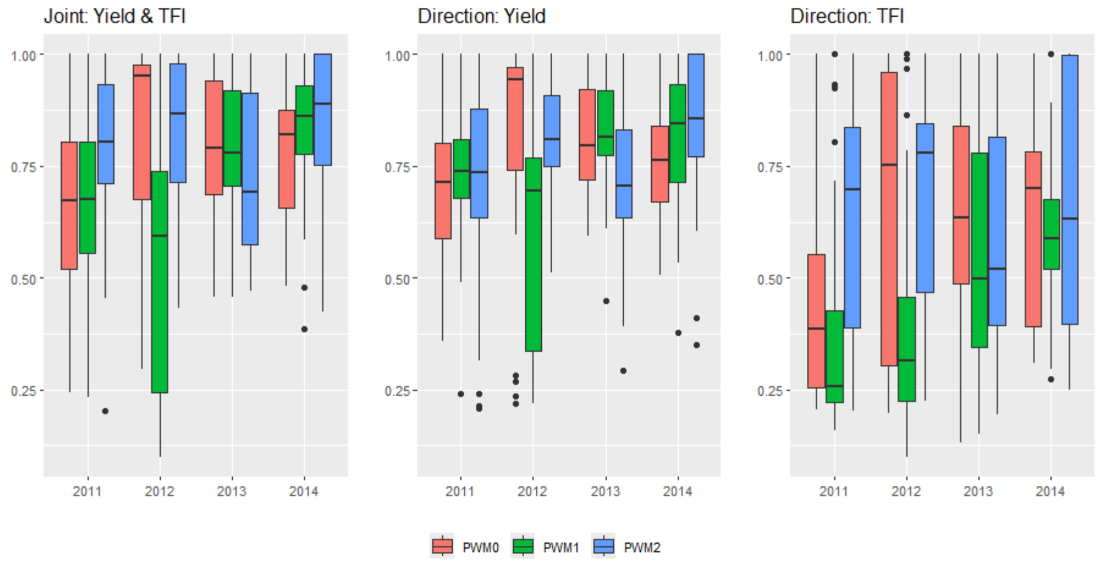


**Figure 3: Efficiency scores by year and PWM practices**

## 5. Summary and outlook

Our results indicate that while production with and without inversion tillage can perform similarly in terms of yields, we find notable differences in terms of herbicide application. Fields with inversion tillage show herbicide reduction potentials of 35% on average compared to 50% for fields without inversion tillage. Metatechnology ratios further suggest that some of these improvement potentials are only available through switches from non-inversion to inversion tillage. As optimal yield levels indicated by the frontiers are similar under inversion tillage and without inversion tillage, our results suggest that herbicide reduction does not necessarily come at the cost of yields.

Comparing different levels of PWM, our results suggest that preventive weed management practices can help to reduce herbicide application without sacrificing yields. In particular, we find the lowest herbicide reduction potentials if multiple PWM strategies are implemented. Additionally, metatechnology ratios are highest under multiple PWM strategies suggesting that those fields shape the production frontier providing the highest yields for a given level of input, including herbicides. Therefore, keeping all other factors constant, optimal yield levels and the lowest herbicide application can be achieved if multiple PWM strategies are applied. Consistent with the literature (e.g., RIEMENS et al., 2022), our results thus indicate that PWM necessitates a holistic strategy comprising multiple practices to reduce herbicide dependence without compromising yields.

Our analysis also indicates that fields operated without PWM practices considered in our study (crop alteration, tillage) show similar improvement potentials in terms of yields and TFI as fields with multiple PWM practices. In contrast, we find fields under only some PWM practices to perform worse with respect to both yields and herbicide application than fields with none or multiple PWM practices. Therefore, our results suggest that a selective application of PWM practices may have negative effects on yields and on required herbicide application. To realize herbicide reduction potentials, implementing either no PWM practices or adopting additional ones is required.

Our results suggest a strong heterogeneity in herbicide reduction and yield improvement potentials. First, we find substantial variation over time – also within PWM groups – in particular concerning herbicide reduction potentials. Although our results are based on comparing only field-level data from the same year in close geographical proximity, an impact of heterogeneous agroclimatic conditions cannot be ruled out. Second, all analyses indicate substantial improvement potentials in terms of herbicide application. Irrespective of the PWM strategy, implementation of best practices can reduce herbicide use substantially by 36-37%.

At first glance, the minor difference in herbicide use efficiency between no PWM and multiple PWM strategies is surprising. The use of pre-crop glyphosate in conventional (PWM0) strategies, which decreases follow-up herbicide use, offers one possible explanation (ANDERT et al., 2018). Under a potential ban of glyphosate, this would suggest that the implementation of multiple PWM practices could provide an alternative delivering similar yields without increasing herbicide use. Plot-specific information on the applied herbicides is currently added to the dataset to further investigate this issue.

We further note the following limitations of our study that we plan to address: While the TFI provides a reasonable measure of the treatment frequency with respect to herbicides, this measure disregards the actual pesticide load by aggregating pesticides irrespective of their active ingredients (KUDSK and JENSEN, 2014). We therefore consider measures that better reflect the actual environmental burden of herbicide application, such as the pesticide load index. Second, our results are based on the assumption that variations in weed pressure are directly linked to the PWM levels, whereas the actual level of weed pressure is unobserved. Other unobserved (or uncontrolled) characteristics such as agro-climatic conditions impacting the weed pressure may thus introduce biases. We therefore plan to investigate in more detail the actual weed pressure accounting for the interplay of local soil conditions and agroclimatic conditions. Third, a potential bias in our results may arise due to the estimation of a convex technology set with ratio measures, as these may introduce non-convexities in the technology (OLESEN et al., 2015). Further robustness checks with the non-convex robust order-m estimator, however, indicate similar efficiency rankings of the observations suggesting only small impacts of the convexity assumption.

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