

An Attempt to Optimize Yield Maps by Comparing Yield Data from a Plot Combine and from a Combine Harvester

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ABSTRACT

This paper deals with yield maps derived from yield monitor data of a combine harvester. Every value of the yield map is determined by robust fitting of a paraboloid surface over a spatial neighborhood around the point to be mapped, so that the influence of outliers is bounded or canceled completely. The neighborhood used looks like the top view of the shape of the wings of a butterfly gliding along the harvest tracks. To determine the optimal size and shape of the neighborhood, an experiment was conducted with yield data measured by a plot combine (called as true values) as well as yield monitor data from a commercial combine with a wider head, which then harvested the same stretch behind the plot combine. The commercial combine was equipped with two monitors. The yield maps are considered to have been optimized if the mean squared deviations (mean squared error) between the true and mapped values has been minimized. A large neighborhood proved necessary for both yield monitors, with the result that the best yield maps obtained appear to be very smooth. Both yield maps could be optimized further by rescaling the yield map values so that their dispersion increases.

Keywords: Yield mapping, paraboloid surface, butterfly neighborhood, farm machinery.

1. INTRODUCTION

Since the appearance of yield sensors researchers are confronted with the problem of how to generate the best yield map that can be obtained based on yield data from combine-mounted, geo-referenced monitors. These data are not only affected by naturally occurring and management-induced yield variation, but also by measurement errors caused by the monitoring process itself (Simbahan et al., 2004). Such errors include grain flow and other sensor errors (moisture, speed, swath width), errors due to geo-referencing and combine movement, operator errors and data processing errors (Shearer et al., 1997; Blackmore & Moore, 1999; Maertens et al., 2001; Arslan & Colvin, 2002). Therefore, various filtering techniques for postharvest processing have already been proposed. The errors can be detected if assigned measured values like GPS points or values for the moisture are unusual, but also if the yield measurements themselves are unrealistic or deviate too much from their neighboring values. Such outlying observations are usually removed before further processing (Shearer et al., 1997; Beck et al.,

1999; Thylén et al., 2001; Lee et al., 2005) or replaced by an estimate based on neighboring yield data points (Noack et al., 2003, Bachmaier and Auernhammer, 2004, 2005). The corrected data are then used to generate the yield map.

Moving neighborhoods are often used to judge if a measurement is an outlier. Their shape is usually based on the Euclidean metrics that result in a circular neighborhood (Thylén et al., 2001; Bachmaier and Auernhammer, 2004). However, the neighborhood of Simbahan et al. (2004) looks like a crossband and that of Noack et al. (2003) is similar to the letter “H”, where the vertical lines of this letter correspond to the neighboring harvest tracks. This is advantageous as measurements of neighboring tracks are independent of the value to be judged.

A yield map generated based on circular neighborhoods was not sufficiently smooth across the harvest tracks, therefore, Bachmaier and Auernhammer (2005) and Bachmaier (2007) used neighborhoods that were wider perpendicular to the direction of travel than they were along it.

The method of Bachmaier (2007) is related to moving „butterfly“ neighborhoods. These look like the top view of the wings of a butterfly gliding along the harvest tracks. The neighborhoods move with the point to be mapped, which corresponds to the butterfly’s midpoint. Each yield map value was determined by a paraboloid surface fitted on this neighborhood, whose shape was assumed fixed, namely twice as large across the tracks (the width of the wings) than along them. The greater the neighborhood, the smoother the map is. To find an adequate smoothness, the neighborhood size was chosen such that the variance of the yield map values equaled the estimated variance of the true yields, which is the difference between the variance of the raw yield data and the error variance of the yield monitor. It was estimated using a robust variogram.

The determination of an optimal neighborhood and, thus, the optimal smoothness is an unresolved problem in yield mapping. A map that is too smooth does not show the yield variability sufficiently, so it misses the target of precision agriculture, but a map that is too detailed does not only detect naturally occurring and management-induced yield variation; it also contains the measurement errors, which should be smoothed out. Statistical methods like kriging or variance comparison (Bachmaier, 2007) are based on assumptions that are never completely fulfilled. An idea of the optimal smoothness can better be obtained by comparing the monitored values, from which the yield map is generated, with reference values that can be considered as the true ones.

Such an attempt of optimization was first undertaken in Bachmaier and Auernhammer (2005) for the measuring system Data Vision Flowcontrol. The two-step yield mapping method described there involves the replacement of outliers by estimates in the first step using moving butterfly neighborhoods. The second step, which generates the yield map, is based on moving elliptical neighborhoods. The shape of these neighborhoods was also chosen twice as large across the tracks than along them, but the sizes of these neighborhoods were optimized by information from an experiment that provided reference values from a plot combine, as well as monitor values from a commercial combine (Figure 1). For this, extensive testing was necessary.

The study presented here refers to the same experiment, but to the one-step method described in Bachmaier (2007), where each yield map value is determined by the fit of a paraboloid surface on a butterfly neighborhood. The goal is to optimize not only the size, but also the shape of the butterfly neighborhood, and this will be done for both measuring systems with which the commercial combine was equipped.

2. MATERIALS AND METHOD

2.1 The Lamprechtsfeld Experiment

In 2004, an experiment was done on a part of the “Lamprechtsfeld”. This field is located at the Thalhausen experimental station, part of the Technische Universität München, Germany, where measured yield values were obtained from a plot combine (called as “true values”), as well as yield monitor data from a commercial combine. For this, every harvest track that did not contain a tramline was harvested twice. It was begun with a plot combine with a cutting width of 2 m, the width of the plots. The length of each harvested plot was 10 m, but to obtain some data with greater spatial resolution, a plot length of 5 m was chosen at three tracks in the middle of the field. Then the same stretch was harvested again with a commercial combine with a wider head; its cutting width was 4.50 m (see Figure 1). The commercial combine was equipped with two yield monitors, Data Vision Flowcontrol (Massey Ferguson), which uses radiometric mass flow measurement, and AgLeader PF 3000, which uses a mass flow measurement impact plate. The harvested crop was summer wheat.



Figure 1. The plot combine was followed by a commercial combine with two yield monitors and a wider head, which also picked up the straw left behind by the plot combine.

2.2 Optimization Criteria

The main task is to choose the size and shape of the butterfly neighborhood such that the average squared difference between plot yields (the true values) and the corresponding yield map is minimized. The yields were transformed to dry matter and expressed as a percentage of their average at the midpoints of the plots (Figure 5 and 6). The use of percentages enables us to quantify the accuracy of the map based on the two yields in terms of the average squared difference or the root of it, which is a root mean squared error:

$$\text{RMSE}_{\text{map-plot}} = \sqrt{\frac{1}{n_{\text{plot}}} \sum_{i=1}^{n_{\text{plot}}} (\text{yield}_{i,\text{map}} - \text{yield}_{i,\text{plot}})^2} \quad (1)$$

2.3 The Yield Mapping Method

The yield mapping method is described in Bachmaier (2007), and a brief summary only is given here.

Each point (x,y) on the map is assigned a regression value from fitting a paraboloid yield surface (Figure 2) in a neighborhood of (x,y) . The regression is robust, so large outliers, which often occur in yield monitor data, have no influence on the estimate, and the yield map can be generated in one step.

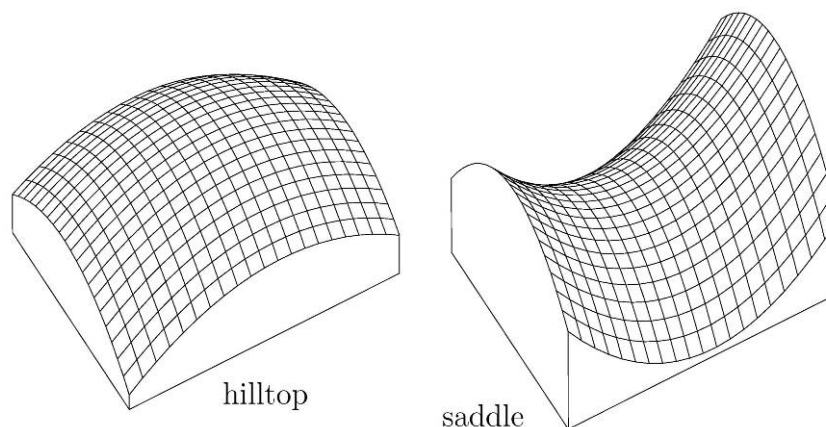


Figure 2. Examples of two types of paraboloid surfaces

The regression is weighted and observations which are likely to be outliers are downweighted (global weights) and so are data points close to the border of the selected neighborhood (local weights). The final weights result from the global and local ones. Global weights $W_i < 1$ are data points where the combine entered the harvest tracks (Figure 4) or those close to a preceding harvest track. The local weights decrease linearly from 1 in the middle to zero at the border of the selected neighborhood (Figure 3).

Since values close to the border of the neighborhood of (x,y) have less influence on the regression, an effective number, \tilde{n} , is introduced rather than treating all values equally. The more weights that are close to 1, the larger this effective number is and the more efficient is a scale estimator that measures the dispersion of the monitored yields around the fitted paraboloid yield surface. Therefore, the chosen local weight function for estimating the dispersion decreases more gradually to zero. More details are found in Bachmaier (2007).

2.4 The Butterfly Neighborhood

The neighborhood used for estimating the paraboloid yield surface looks like a butterfly gliding along the tracks (Figure 3). Its length is shorter at the body than it is at the wings. It is thus easier to ensure, by using robust M-estimates, that harvest tracks consisting of many erroneous values cannot have too much influence on the fitted yield value even if these tracks are close to the point to be mapped.

Figure 3 shows butterfly contour lines from weight 0 (outside) to weight 1 in increments of 0.2.

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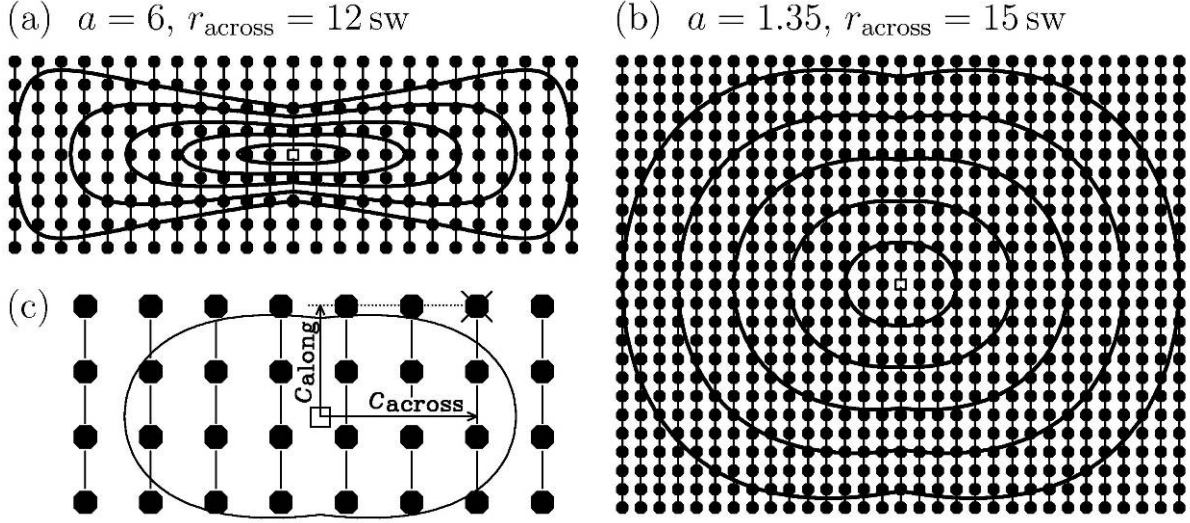


Figure 3. (a) and (b) Contour lines of equal butterfly distance for different butterfly parameter a and different neighborhood radii r_{across} in units of swath widths (sw)
(c) The components c_{across} and c_{along} for calculating the butterfly distance between the point to be mapped, which is indicated by a square, and the logged point, which is marked by a cross, according to the definition in (2)

The full weight 1 is only reached by the butterfly's midpoint (x, y) , where the yield map value is generated. It is denoted by a square. The contour lines consist of points (x_i, y_i) whose “butterfly distance” is constant. Such a distance measure is defined using a “butterfly parameter”, a . The butterfly parameter is the ratio of “radius” (half width) across the harvest tracks to that along them at the point to be mapped where it is not the longest one, as Figure 3 shows. Figure 3 (a) provides $a = r_{\text{across}}/r_{\text{along}} = (12 \text{ sw})/(2 \text{ sw}) = 6$, and $a = r_{\text{across}}/r_{\text{along}} = (15 \text{ sw})/(11.1 \text{ sw}) = 1.35$ is obtained in Figure 3 (b); sw is the swath width. The butterfly distance between (x, y) and a point (x_i, y_i) of the neighborhood is defined as follows:

$$d_{\text{butterfly}}((x_i, y_i), (x, y)) := \sqrt{c_{\text{across}}^2 + \left[a - \frac{|c_{\text{across}}|}{r_{\text{across}}} (a - 1) \right]^2 c_{\text{along}}^2} \quad (2)$$

where c_{along} and c_{across} are the decomposition components of the usual (Euclidean) distance, d , between the points (x, y) and (x_i, y_i) along and across the harvest tracks. They can be calculated from neighboring data points on the harvest track of (x_i, y_i) . These are usually the points before and after, (x_{i-1}, y_{i-1}) and (x_{i+1}, y_{i+1}) , where the calculation is as follows:

$$c_{\text{along}} = \frac{(x_i - x)(x_{i+1} - x_{i-1}) + (y_i - y)(y_{i+1} - y_{i-1})}{\sqrt{(x_{i+1} - x_{i-1})^2 + (y_{i+1} - y_{i-1})^2}} \quad (3)$$

$$c_{\text{across}} = \frac{(x_i - x)(y_{i+1} - y_{i-1}) - (y_i - y)(x_{i+1} - x_{i-1})}{\sqrt{(x_{i+1} - x_{i-1})^2 + (y_{i+1} - y_{i-1})^2}} \quad (4)$$

Figure 3 (c) shows these components for that neighboring point (x_i, y_i) which is marked by a “x”.

3. OPTIMIZATION RESULTS

3.1 Large Areas with a Global Weight Less than One

Because the experimental field was small, the proportion of the area where the combine entered harvest tracks was larger than usual. The first six (Flowcontrol), respectively the first 15 (AgLeader) positive yield data points of every track were assigned a global weight of zero as they are incorrect. These weights were computed and assigned to each data point in a pre-processing step that detected the start and end points of tracks as well as partial cutting widths by analyzing the GPS data. Following the method used by Steinmayr (2003), zero-yields were omitted. Figure 4 shows the global weights of the “Lamprechtsfeld” experiment. They depend only on the GPS coordinates of the data points. Details for calculating the global weights are given in Bachmaier (2007).

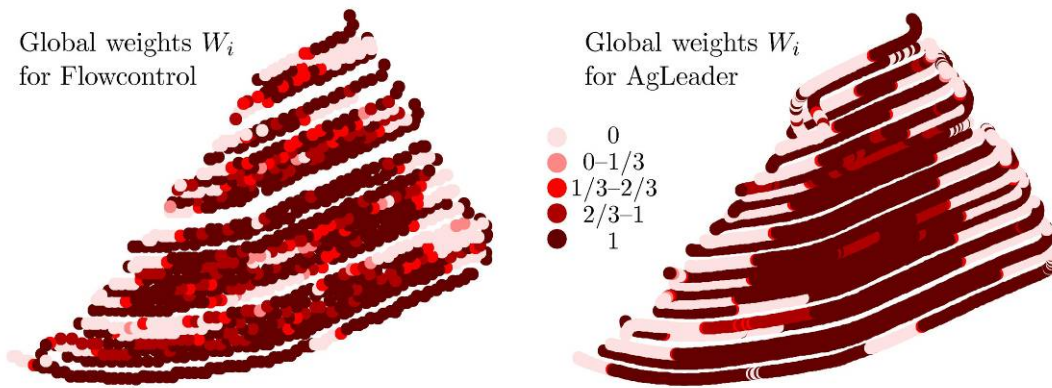


Figure 4. Global weights W_i for the GPS coordinates recorded by Data Vision Flowcontrol (left) and AgLeader (right).

3.2. Minimizing the Root Mean Squared Error

The smallest root mean squared error, $RMSE_{map-plot}$, for the monitor Data Vision Flowcontrol, which has a data logging frequency of about 0.3 Hz, was with an effective number of data points of $\tilde{n} \approx 120$ and a butterfly parameter of $a \approx 6$ (Figure 3 (a)). This corresponds to an r_{across} of at least 12 times the cutting width (cw), to the value 4.30 m (the head width was 4.50 m) was assigned, and to an r_{along} that usually equals about twice the cutting width, provided that there are enough data around the point to be estimated, so that the butterfly neighborhood need not exceed the extent of test field.

The AgLeader monitor has a data logging frequency of 1 Hz, which is about three times as big as that of the Flowcontrol monitor, so there are about three times as many yield records. But to minimize $RMSE_{map-plot}$, a \tilde{n} of even 1000, which is more than a triplication, and a butterfly parameter of only $a \approx 1.35$ (Figure 3 (b)) proved necessary. It was reached for $r_{across} \approx 15$ sw and $r_{along} \approx 11$ sw in the middle of the experimental field. This might be because the Flowcontrol data have been smoothed by an internal algorithm, and probably comprise previous measurements from the same harvest tracks. Because this filtering is not done with the AgLeader data (see Figure 7), a longer length along the tracks is necessary to compensate for the errors.

The butterfly neighborhoods for both yield monitors are large, as shown in Figure 3 (a) and (b). However, they are used to map the yields using weighted regression (Section 2.3) where only data points in the nearer neighborhood have a weight close to one; the weight of values close to the boundary of the selected neighborhood has almost decreased to zero, as indicated by the contour lines in Figure 3.

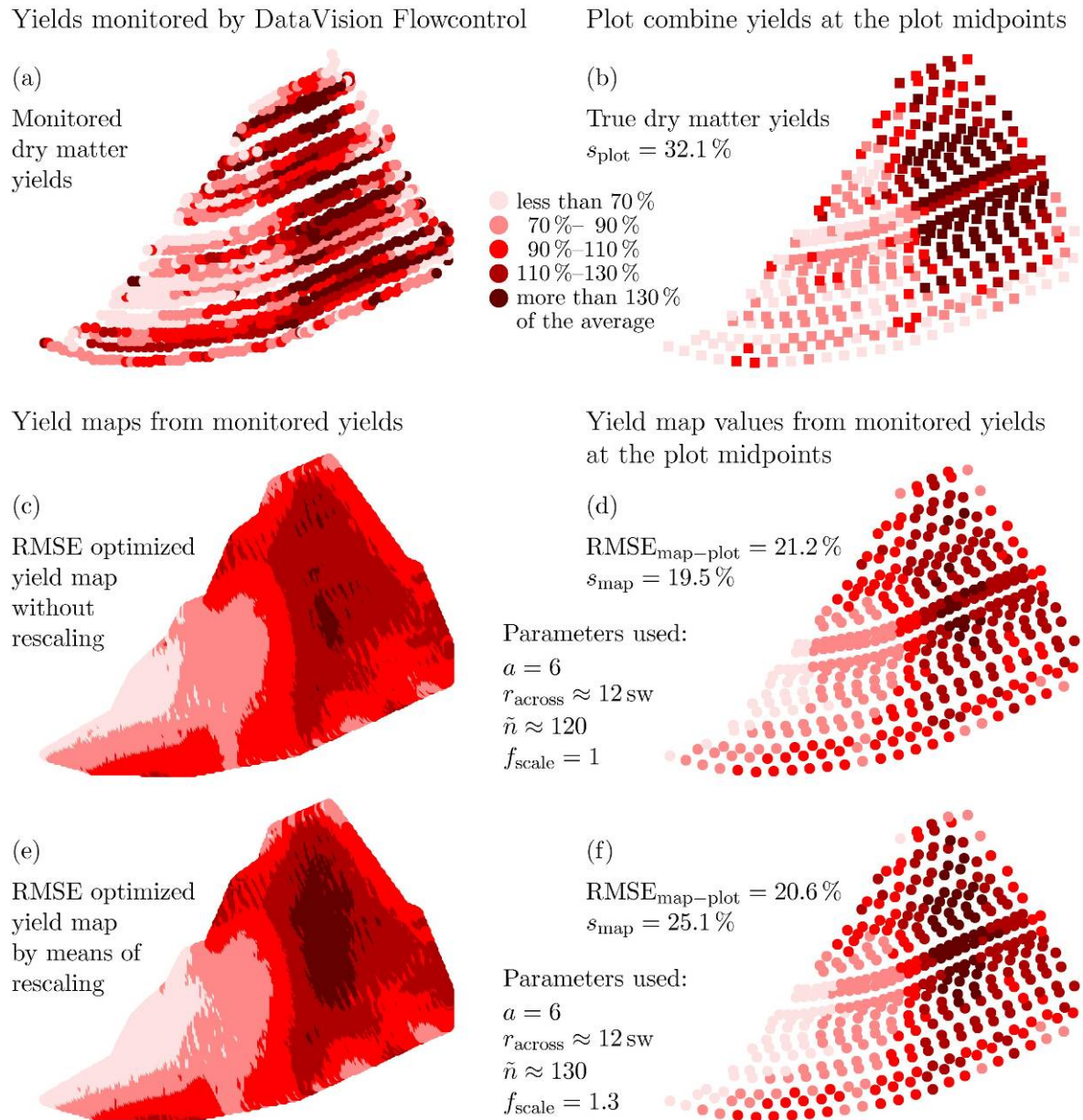


Figure 5. Comparison of percentage dry matter yields of the plot combine and the corresponding yield map values for the Data Vision Flowcontrol monitor

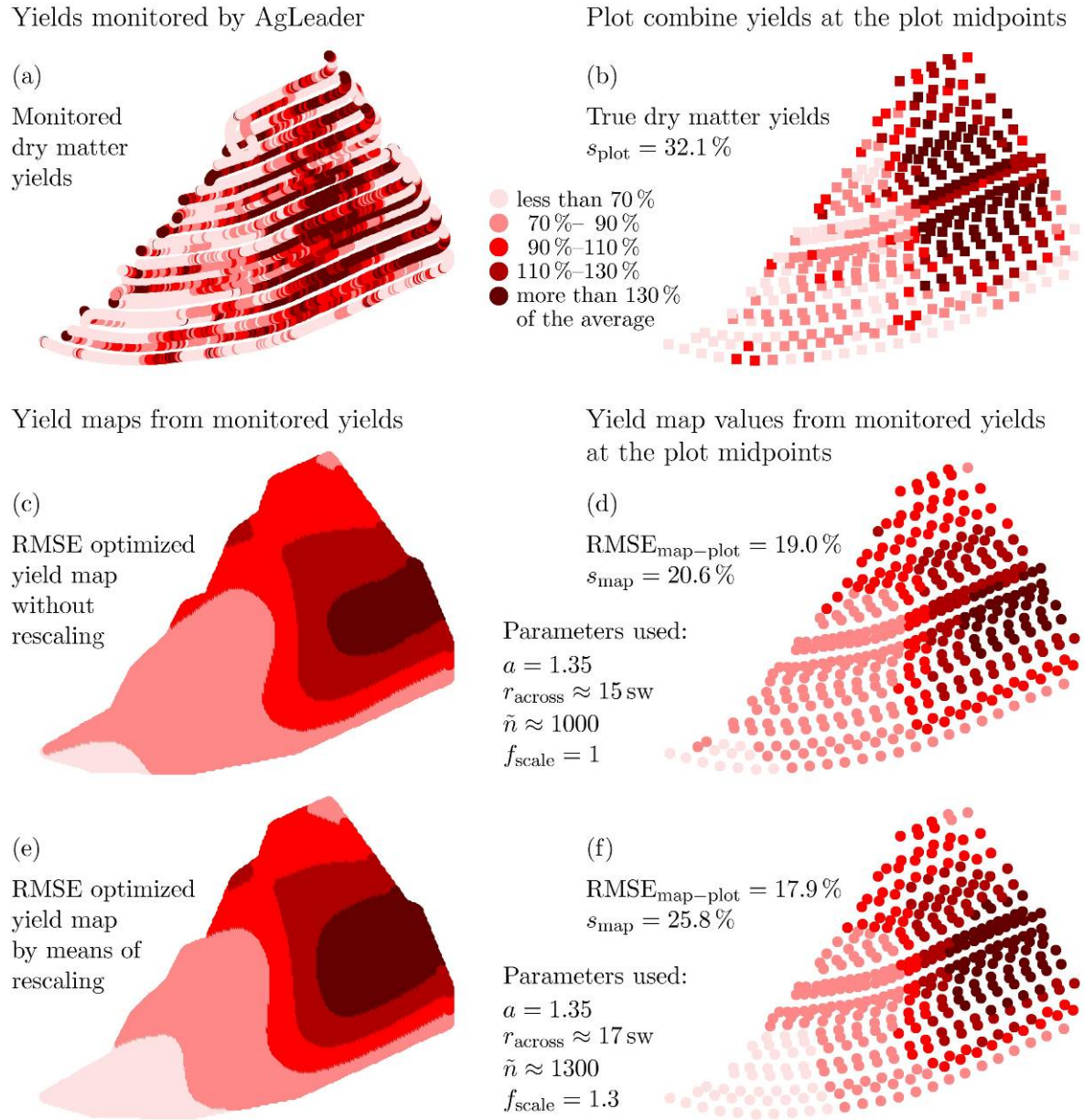


Figure 6. Comparison of percentage dry matter yields of the plot combine and the corresponding yield map values for the AgLeader monitor

Figure 5 (c) and 6 (c) show the yield maps resulting from these butterfly neighborhoods. Contrary to the AgLeader yield map in Figure 6 (c), the Flowcontrol yield map in Figure 5 (c) has some lines across the tracks that result from the large a and the short distance along the tracks in the middle of the butterfly, and so the variability along the tracks is greater than it is across them.

The minimized root mean squared errors are $\text{RMSE}_{\text{map-plot}} = 21.2 \%$ for the Flowcontrol map and $\text{RMSE}_{\text{map-plot}} = 19.0 \%$ for the AgLeader map. The latter is more accurate. The standard deviation

of the yield map values at the midpoints of the plots is $s_{\text{map}} = 19.5 \%$ for the Flowcontrol map and $s_{\text{map}} = 20.6 \%$ for the AgLeader map; both are considerably smaller than the standard deviation $s_{\text{plot}} = 32.1 \%$ of the corresponding plot yields, which are considered to be the true values. For a large area, not only are the measurement errors smoothed, but so is the field variability. Compared with the plot yields, large yields are underestimated and small yields are overestimated. Nevertheless, the mean squared error was minimized by such neighborhoods, and consequently the best yield map obtained with yield monitor values has lost much variability. Thus, it is a compromise between error smoothing and detecting yield variability.

3.3. Further Optimization by Rescaling

Figure 7 is taken from Steinmayr (2003). It shows the flow rate behavior of the yield monitors Flowcontrol and Agleader, which were used in the Lamprechtsfeld trial, and the yield monitor RDS-Ceres2 (light barrier, volumetric flow measurement) from test bed trials, which have the following four rotating flow rate levels: 30 Mg h^{-1} , 20 Mg h^{-1} , 30 Mg h^{-1} , 10 Mg h^{-1} . Note that the units are here Megagrams per hour.

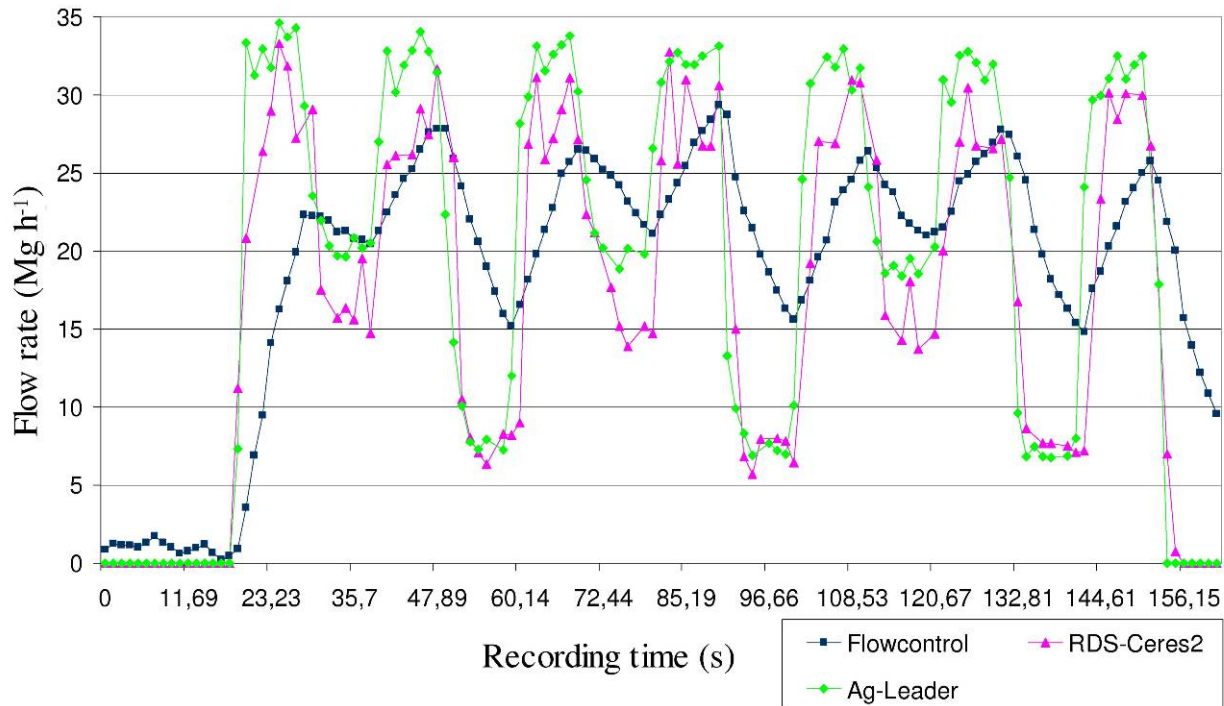


Figure 7. Behavior of three yield monitors at moving flow rates measured in test bed trials (by Steinmayr 2003)

As mentioned above, Figure 7 shows that the Flowcontrol monitor contains a strong smoothing algorithm because the 10 seconds where the flow rate remains the same is not enough to reach the yield of this level. To counteract this phenomenon, we can change the relative yields by using a scale factor:

$$\text{yield}_{i,\text{map}} := 100 \% + f_{\text{scale}}(\text{yield}_{i,\text{fitted}} - 100 \%). \quad (5)$$

$\text{yield}_{i,\text{fitted}}$ is the yield that arises from fitting the paraboloid yield surface on the butterfly neighborhood, and f_{scale} is the scale factor to be optimized. For example, a scale factor of $f_{\text{scale}} = 2$ changes the data $\text{yield}_{i,\text{fitted}} = 90\%$, 100% , 110% to the values $\text{yield}_{i,\text{map}} = 80\%$, 100% , 120% . If a negative value occurred, it would be assigned the value 0.

Using $f_{\text{scale}} = 1.3$, $\tilde{n} \approx 130$ and $a = 6$, the root mean squared error of the Flowcontrol monitor could only be reduced from 21.2% to 20.6% . Figure 5 (e) shows the yield map resulting from these parameters. Although Figure 7 suggests that the AgLeader data do not need to be stretched by a scale factor, the same $f_{\text{scale}} = 1.3$ proved adequate to minimize the root mean squared error of the AgLeader map (Figure 6 (e)). This minimization requires an effective number of $\tilde{n} \approx 1300$, compared with the previous value of 1000, and $a \approx 1.35$ remained the same. The root mean squared error was only reduced from 19.0% to 17.9% . However, the standard deviation of the yield map values at the midpoints of the plots increased from 19.5% to 25.1% for the Flowcontrol map and from 20.6% to 25.8% for the AgLeader map. These standard deviations are still smaller than the corresponding ones of the plot yields (32.1%). Thus, the best yield map obtained with yield monitor values and the help of an optimized scale factor has still lost variability. But this is not surprising since the moving neighborhoods used to optimize the yield map were very large, so that the yield map turned out to be very smooth, and smoothing reduces the variance of the map.

4. DISCUSSION AND CONCLUSIONS

In spite of various problems with the yield monitors, our method aims to generate maps that are as close as possible to the true values. Nevertheless, the yield maps from Data Vision Flowcontrol and AgLeader, show remarkable differences. This demonstrates that it is difficult to find a method that is universally applicable to different yield monitors.

One problem at the Lamprechtsfeld trial was that the commercial combine, with a head of 4.50 m was not operating at capacity because a width of 2 m had been cut out by the plot combine and it harvested a proportion of less than 56% of the cutting width. However, according to the experts of the combine colloquium in Dresden (March 2007), the decisive criterion for the accuracy of the measurements is the whole mass that was picked up by the combine. Since the combine also picked up the straw that the plot combine has left behind, the accuracy of the monitored results should not be affected much. Nevertheless, the areas harvested by the plot combine, which are the central two meters of every harvest track, are not exactly the same as those harvested by the commercial combine, which are the borders of every harvest track (Figure 1). This means that even if the monitors were very accurate, there would be differences from the values of the plot combine. Since monitored yield data are less accurate, it would be advantageous if the width harvested by the commercial combine were considerably greater than that harvested by the plot combine. This could be reached if we used a commercial combine with a 6 m or even a 9 m wide head and a plot combine with a smaller cutting width (e.g. 1.50 m).

The main problem with the experiment could have been that the harvested area was very small. Increasing it would diminish the proportion of area where the combine enters the harvest tracks, and the proportion of erroneous measurements would be reduced. Besides, the Lamprechtsfeld trial suggests the use of large neighborhoods for optimizing the yield map values. This especially requires a large trial area. However, the Lamprechtsfeld experiment was restricted to a small part

of the Lamprechtsfeld, so the selected butterfly neighborhood of most yield map points exceeded the extent of test field. If the test area had been larger, more yield map points could have been mapped based on neighborhoods with smaller radii.

As far as the Data Vision Flowcontrol monitor is concerned, the use of a scale factor of about 1.3 seems justified because Steinmayr's (2003) test bed trials confirm that the Flowcontrol monitor uses a strong smoothing algorithm (Figure 7), and a scale factor $f_{scale} > 1$ would counter this effect. For the AgLeader monitor, however, a scale factor greater than one appears questionable. Steinmayr's test bed trials rather suggest the opposite because flow rates of 30 Mg h^{-1} are overestimated and those of 10 Mg h^{-1} are underestimated. On the other hand, Steinmayr's test bed trials also show that the AgLeader monitor is less accurate for flow rates less than 10 Mg h^{-1} . The latter might have occurred in the Lamprechtsfeld trial as a stretch of 2 m was cut out of every track. To state the finding concerning the use of a scale factor, lots of trials like that on the Lamprechtsfeld should be done for different types of monitors, combines and yield levels.

What we venture to say on the basis of this one trial is that commercial yield monitors are not yet adequate to fully represent underlying variability in crop yield; the variance of the optimized map did not reach that of the plot values. But the yield maps in Figure 5 and 6 also show that commercial yield monitors are able to show the main structure of a field.

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