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RESEARCH LETTER

Evaluating how operator experience level affects efficiency gains for precision agricultural tools

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Abstract

Tractor guidance (TG) improve environmental gains relative to nonprecision technologies; however, studies evaluating how tractor operator experience for nonguidance comparisons affect gains are nonexistent. This study explores spatial relationships of overlaps and gaps with operator experience level (0–1, 2–3, 6+ yr) during fertilizer and herbicide applications based on terrain attributes. Tractor paths recorded by global navigation satellite systems were used to create overlap polygons. Results illustrate operator experience level is critical for better efficiency gains estimation (for non-TG comparisons). Operators with 6+ yr of experience reduced overlap by 7.7 and 20.6% compared with operators with 2–3 and 0–1 yr of experience, respectively. New operators had consistently higher overlap across all slope (<0.5, 0.5–1, 1–2, 2–5, 5–9, and 9–15%) and roughness classes (<0.1, 0.1–0.2, 0.2–0.3, 0.3–0.5, 0.5–0.7, 0.7–1 and >1). A low interpersonal reliability value of 0.02–0.03 indicates operator experience is crucial to estimate TG efficiency gains and consistent drivers experience levels are needed when evaluating economic and environmental gains from TG.

1 | INTRODUCTION

Tractor guidance (TG) systems are a type of precision agriculture technology that uses global navigation satellite systems (GNSS) to mechanically steer tractor paths during field operations. Spatially precise applications of nitrogen (N) and phosphorus (P), through the use of auto-guidance systems, improve crop production and reduce non-point source pollution across agricultural landscapes, relative to non-GNSS enabled technologies (Shockley et al., 2011). Specifically, Kharel et al. (2020a) reported 6 and 16% reductions in input overlaps (double applications) and gaps (no application), respectively, via TG systems. Greater effective spatial coverages can translate to less labor, lower greenhouse gas emissions and non-point source pollution, and greater cost savings per unit area (Lindsay et al., 2018). However, in a follow-up study, Kharel et al. (2020b) found that factors such as terrain attributes (increased slope, variable topography) and field shape and irregularity drive the extent of these efficiency gains relative to non-TG systems. Other important factors, such as operator experience level for the non-TG comparison, likely also affect efficiency gain estimates; however, evaluations of driver experience have not been done to date.

Previous work by Ashworth et al. (2018) found that TG led to total farm-level carbon equivalent emission reductions of 15.7, 3.5, and 9.6 Mg for cotton (*Gossypium hirsutum* L.), soybean [*Glycine max* (L.) Merr.], and cotton–soybean

Abbreviations: GNSS, global navigation satellite systems; IPR, interpersonal reliability; TG, tractor guidance.

mixed operations, respectively. These results highlight that emission reductions are crop, amount, and agro-input specific. Additional work by Ashworth et al. (2022) found that fertilizer source (organic vs. inorganic) greatly affected environmental benefits from TG via a life cycle assessment. In this assessment, poultry litter had fewer environmental gains than inorganic N, owing to the rate of volatilization for poultry litter under IPCC Tier 1 methods (IPCC, 2006) being twice that of synthetic sources, as well as fewer yield gains under the organic source.

This study set out to explore the effect of operator experience level (0–1, 2–3, 6+ yr) during fertilizer (organic and inorganic) and herbicide applications and based on terrain attributes, relative to precision guidance tools. We predicted that the greatest operator experience level (6+ yr) scenario would have the fewest overlaps and gaps and, consequently, the least environmental gains during agro-input applications relative to precision guidance systems.

Core Ideas

- Tractor operator experience level affects overall production efficiencies.
- Operator experience affects total overlap area.
- Efficiency calculations should consider operator experience level.

2 | MATERIALS AND METHODS

2.1 | Field experiment, data collection, and whole field overlap estimation

This study was conducted at Booneville, AR, USA (35.087723 N, 93.993740 W) in 2018 and 2019. The details of the field study, data collection, and overlap estimation methodology for 2018 data are available in Kharel et al. (2020a, 2020b). A New Holland 7040 (NH7040) tractor was used without TG (manually driven) in six fields (11.7–22.5 ha) with a 10-m fertilizer spreader and a 13-m boom sprayer from 2018–2019. Three operator experience levels where Operator A had 6+ yr tractor driving experience, Operator B had 2–3 yr experience, and Operator C had 0–1 yr experience were used for this study. Operator A applied fertilizer in 2018, Operator B applied herbicide in 2019, and Operator C applied fertilizer in 2019 for the same six pasture fields. Intelliview IV display (CNH), 372 receiver, and RTX signal (Trimble Navigation Ltd.) with 15-cm pass to pass accuracy as a navigation system were used by each operator. Kharel et al. (2020a) reported that there was no statistical difference in overlap and gap due to operation (fertilizer and herbicide application); hence, we combined these datasets from both operations to evaluate the effect of driver experience.

Overlap and gap information were calculated as described in Kharel et al. (2020a, 2020b). Briefly, data points (tractor location recorded each second during field operations) showing more than 35° difference in heading direction were assigned a new pass number in increments. A line feature was created for each pass and a buffer polygon around the line feature was developed using equipment width. For each operation within a field, individual pass polygons were sequentially evaluated with the rest of pass polygons and the overlap portions were developed as overlap polygons for further analysis. Gap area was then calculated by subtracting pass polygon and overlap polygon area from the field boundary area as shown by Equation 1 in Kharel et al. (2020a). Both overlap and gap area were expressed relative to field boundary area in percentage for statistical analysis. Since gap area was calculated for whole field and no gap polygons were created within a field, the majority of analysis on this paper focuses on overlap polygons.

2.2 | Terrain attributes and grid sampling

Terrain attribute data for the study site were prepared at 10- × 10-m resolution after resampling of (1- × 1-m) elevation data derived from laser sensor Light Detection and Ranging (LiDAR, USDA-Geospatial Data Gateway, https://datagateway.nrcs.usda.gov) as described in Kharel et al. (2020b). Terrain attributes slope (Horn, 1981) and roughness (Wilson et al., 2007) affected overlap in a previous study (Kharel et al., 2020b), and hence we further explored these attributes with respect to driver experience in this study. Briefly, a 50- × 50-m sampling grid was overlaid on top of terrain attribute raster (slope and roughness index) and overlap polygon. Within each 2,500-m^2 grid (6,565 total number of grid samples), average overlap area and median terrain attribute values were extracted. Terrain attribute values were classified into six (slope) and seven (roughness) classes based on range of value extracted. Average overlap area per grid (m^2/2,500 m^2) for each terrain class was calculated. A total of 85 observations for slope and 116 observations for roughness class were used to evaluate how driver experience level interacts with terrain to affect overlap (relative to TG-systems). R (R Core Team, 2021) computing environment with the 'raster' (Hijmans, 2021) package was used to resample and calculate terrain attributes.

2.3 | Statistical analysis

A two-step analysis was conducted for inferential statistics. Fixed-effect ANOVA models were developed to estimate operator experience effect on overlap and gap, while random-effect models were used to estimate variance associated with operator and field relative to unexplained variance (error variance):

$$Y_{ij} = \mu + a_i + \varepsilon_{ij};\ \text{with}\ \varepsilon_{ij}\text{i.i.d.} \sim \mathrm{N}\left(0, \sigma^2\right) \tag{1}$$

$$Y_{ijk} = \mu + a_i + b_j + (ab)_{ij} + \varepsilon_{ijk};\ \text{with}\ \varepsilon_{ijk}\text{i.i.d.} \sim \mathrm{N}\left(0, \sigma^2\right) \tag{2}$$

$$Y_{ijk} = \mu + \propto_i + \beta_j + \varepsilon_{ijk};\ \text{with}\ \alpha_i\text{i.i.d.} \sim \mathrm{N}\left(0, \sigma_\alpha^2\right), \beta_i\text{i.i.d.} \sim \mathrm{N}\left(0, \sigma_\beta^2\right), \text{and}\ \varepsilon_{ijk}\text{i.i.d.} \sim \mathrm{N}\left(0, \sigma^2\right) \tag{3}$$

where Y_{ij}/Y_{ijk} is overlap or gap estimate per field or grid sample, μ is grand mean across all the fields or grid samples, a_i is operator fixed effects (i = 1–3), i.i.d. is independent and identically distributed, b_j is terrain attribute (slope or roughness index) fixed effect (j = 1–6 for slope class and 1–7 for roughness class), $(ab)_{ij}$ is operator and terrain attribute interaction fixed effect, $\propto_I$ is operator random effect, β_j is field random effect (j = 1–6), ε is error (random) term, and σ^2 is variance associated with random variables (operator, field and error). Equations 1 and 2 are fixed effect models, and Equation 3 is a random-effect model.

Operator experience, slope class, roughness class and their interactions were considered fixed factors while fields and grids (with 'Grid sample' data) were considered random replication in fixed effect models (Table 1, Models 1–5). In the random-effect model (Table 1, Models 6–7), both field and operator experience were considered random factors. Models 1, 2, and 6 were developed using whole field dataset (6 fields × 3 operators = 18 observations), Models 3 and 7 were developed using all 50- × 50-m grid samples (6,565 total observations), and Models 4 (85 observations for slope class) and 5 (116 observations for roughness class) were developed after classifying each grid within a field to one of the terrain attributes classes. For each model, null hypothesis (effect column) was tested against $P < .05$ (Pr > F column). All models were developed using R computing software. R package 'lme4' (Bates et al., 2015) was used to develop random-effect models.

Variance extracted from random-effect models (Models 6–7) was used to develop interpersonal reliability (IPR, Bartlett & Frost, 2008; Kharel et al., 2019) as follows:

$$\text{IPR} = \frac{\text{Field variance}}{\text{Field variance} + \text{Operator variance} + \text{Error variance}} \tag{4}$$

The IPR value ranges between 0 and 1, with higher values indicating better reliability among operators.

3 | RESULTS AND DISCUSSION

3.1 | Operator experience level effect on efficiency gains for TG-Off comparison

Operator experience level affected overlaps at both whole-field (Table 1, Model 1) and grid-sample levels (Table 1, Model 3). Overlap differed ($P < .05$) by 7.8, 15.5 and 28.4% for Operator A, B, and C, respectively, at whole-field levels (Figure 1a). This result suggests an experienced operator reduces overlap by 7.7 and 20.6% compared with a driver with 2–3 yr experience and new operator, respectively. Similarly, at a grid-sample scale (per 2,500-m^2 area), overlap increased ($P < .05$) by 17.7, 68, and 88 m^2 for Operator A, B, and C, respectively. This suggests again a large increase in overlapped field areas receiving agro-chemical application from Operator A to B and C, suggesting drivers' experience level is an important factor for TG efficiency gain calculations.

Gap area (% relative to field boundary) was not affected ($P > .05$) by operator experience levels (Table 1, Model 2), and averaged 25.2, 21.6, and 23.6% of field boundary area for Operator A, B, and C, respectively (Figure 1b). Kharel et al. (2020a) reported overlap of 3–11% and gap of 15–31% in these fields when TG was off previously. The large gap on these fields was explained as the result of unavoidable obstacles (tree, ponds, etc.).

Kharel et al. (2020a) reported an overall efficiency gain (spatial coverage) of 8% by TG system over non-TG system. Calculation was based on the most-experienced operator (6+ yr). If we use driver experience effect on those calculations, efficiency gains will be much higher with non- or less-experienced operator as illustrated above by 7.7–20.6% more overlap by these two operators.

3.2 | Terrain attributes and operator experience level effect on overlap

Interaction between terrain attribute slope class and operator experience was observed for overlap area (Table 1, Model 4). Overlap area ranged from 14 m^2 per grid (2,500 m^2) for Operator A with slope class 1–2% to 196 m^2 for Operator B with slope class 9–15%. Operators B and C had higher overlap at each slope class compared with Operator A (Figure 1c).

TABLE 1 Analysis of variance using fixed-effect and random-effect models based on operator experience level (0–1, 2–3, 6+ yr) from 2018 to 2019 during herbicide and fertilizer applications (six fields total) at the USDA-ARS Dale Bumpers Small Farms Research Center in Booneville, AR

Fixed effect model									
Model no.	**Method**	**Response variable**	**Effect**	**nDF**	**dDF**	**Sum square**	**Mean square**	***F* value**	**Pr (>*F*)**
1	Whole field	Overlap %	Operator	2	15	1,300.77	650.38	7.58	0.005
2	Whole field	Gap %	Operator	2	15	37.84	18.92	0.45	0.643
3	Grid sample	Overlap area	Operator	2	6,562	5,804,020	2,902,009.78	404.70	0.000
4	Grid sample	Overlap area	Operator	2	67	51,875.47	25,937.73	28.98	0.000
4	Grid sample	Overlap area	Slope	5	67	8,464.54	1,692.90	1.89	0.107
4	Grid sample	Overlap area	Operator × slope	10	67	25,941.39	2,594.13	2.89	0.005
5	Grid sample	Overlap area	Operator	2	95	98,763.05	49,381.52	49.11	0.000
5	Grid sample	Overlap area	Roughness	6	95	3,911.99	651.99	0.64	0.691
5	Grid sample	Overlap area	Operator × roughness	12	95	11,087.92	923.993	0.91	0.531
Random effect model									
Model no.	**Method**	**Response variable**	**Effect**	**Variance**	**Error variance**	***N***	**IPR**		
6	Whole field	Overlap %	Field	5.99	79.72	18	–		
6	Whole field	Overlap %	Operator	95.11	79.72	18	0.03		
7	Grid sample	Overlap area	Field	187.50	7,003	6,565	–		
7	Grid sample	Overlap area	Operator	1,428.20	7,003	6,565	0.02		

Note. nDF = numerator degree of freedom; dDF = denominator degree of freedom; *N* = number of observations; IPR = interpersonal reliability.

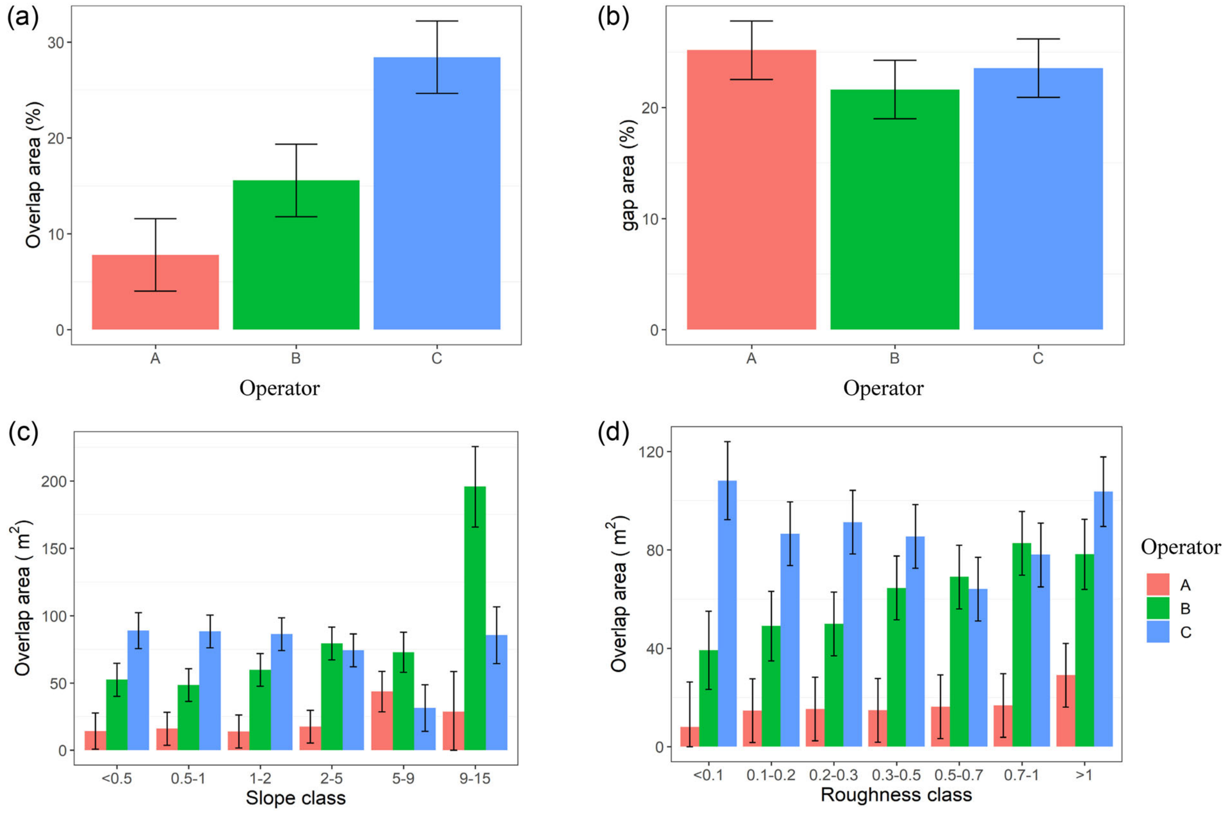

FIGURE 1 Least square means and their standard error after linear (fixed effect) ANOVA model. (a) Overlap area (% to boundary area) by three operators, (b) gap area (% to boundary area) by three operators, (c) overlap area (m^2/2500 m^2 grid) by three operators for slope class, and (d) overlap area (m^2/2500 m^2 grid) by three operators for each roughness class. Operators' experience levels were 0–1, 2–3, and 6+ yr. Bars are standard error

Overlap increased for the higher slope class with Operators A and B, as they showed more control in relatively flat area compared with the inexperienced Operator C. Surprisingly, Operator B had very high overlap in greater slopped terrain (slope class 9–15%). Averaged across slope class, overlap area was 22, 85, and 76 m^2 per grid for Operator A, B, and C, respectively. Similarly, averaged across operator, overlap area was 52, 51, 53, 57, 49, and 103 m^2 per grid for slope class <0.5, 0.5–1, 1–2, 2–5, 5–9, and 9–15%, respectively.

Terrain attribute roughness class had no effect ($P > .05$) on overlap area or in interaction with operator experience level (Table 1, Model 5). This could be due to higher variability introduced into the dataset by the inexperienced operator. Averaged across roughness class, operator experience level resulted in different ($P < .05$) overlap for each operator: 16, 62, and 88 m^2 per grid for Operator A, B, and C, respectively. As with slope class, Operators B and C had greater overlap compared with Operator A at each roughness class (Figure 1d). As opposed to previous results, where both slope and roughness classes were important factors determining overlap (with a single-experience operator; Kharel et al., 2020b), the present study introduced more variability by adding an inexperienced operator. Therefore, the interaction of operator with terrain attributes resulted in no effects in our current study.

3.3 | Comparison of variability due to operator

At whole-field levels, 52.6% of total variability (95.1 out of 180.8) was due to operator variability and 44% remained as unexplained error variance (Table 1, Model 6). Hence, IPR among operator was very low (0.03). At the grid-sample level, variability due to operator decreased to 17% (1,428 out of total 8,618), but unexplained error variance increased to 81% (Model 7). Hence, the IPR value further decreased to 0.02 at the grid-sample level. At both scales (field and grid sample), low IPR values indicate that TG efficiency estimation methods should consider operator experience as a critical factor while doing such comparison. Kharel et al. (2019) used a similar approach to compare yield monitor data cleaning consistency among three individuals and, with the observed IPR value between 0.82 and 0.99, concluded person-to-person variability was smaller and results should be comparable. For IPR analysis, when at least three people and 30 samples are involved, values between 0.75 and 0.90 indicate good reliability (Koo & Li, 2016).

4 | CONCLUSIONS

Adoption of TG systems has increased by 50–60% of total acres used to grow major row crops in the United States; however, to date TG technologies are not widely used for either smaller-scale production or pasture-based systems, and more information is needed regarding how efficiency estimates from TG in pasture systems are affected by operator level of experience (for TG-Off comparisons). Three operators with varying experience levels (0–1; 2–3; 6+ yr) applied fertilizer and herbicide on the same six fields from 2018 to 2019. Tractor paths recorded by GNSS were used to create overlap polygons. Results showed that operator experience level is critical when making efficiency gain estimates and operators with 6+ yr of experience reduced overlap 7.7 and 20.6% compared with 2–3 yr of experience and new operators, respectively. Similarly, the experienced operator responded during field operations to field slope and roughness, whereas the inexperienced operator had consistently higher overlap across all terrain attribute classes. A low IPR value (0.02–0.03) indicated that operator experience is crucial to estimate TG efficiency and a similar driver experience level is needed when estimating TG efficiency gains.

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AUTHOR CONTRIBUTIONS

Tulsi P. Kharel: Conceptualization; Data curation; Formal analysis; Methodology; Software; Validation; Visualization; Writing – original draft; Writing – review & editing. Amanda J. Ashworth: Conceptualization; Resources; Supervision; Validation; Writing – original draft; Writing – review & editing. Phillip R. Owens: Conceptualization; Funding acquisition; Investigation; Methodology; Project administration; Resources; Writing – review & editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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