

<sup>1</sup> Living on the edge: crop boundary effects on canola and wheat yields in  
<sup>2</sup> Alberta

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<sup>5</sup> **Abstract**

Field boundaries can improve crop yields by creating better abiotic conditions for crop growth (e.g. moisture, temperature), and can act as refuges for beneficial arthropods. This suggests that beneficial crop boundaries may create an intermediate hump-shaped increase in crop yield, where negative edge effects are cancelled out by increased ecosystem services (e.g. pollination or pest suppression) from the field boundary. However, there is little large-scale evidence showing this, largely because yield is costly and time-consuming to measure. Precision yield data from combine yield monitors has huge potential in this respect, as the equipment is relatively cheap and commonly measured by growers. Average crop yield tended to increase with distance from crop boundaries before plateauing at about 50 m, and yield variation (SD) tended to decrease concurrently with distance. Differences between boundary types tended to be weak and variable, especially for wheat; there was some evidence of certain field boundaries causing a greater decrease in yield at the edge, but these differences tended to be small in magnitude (<5% of yield). Furthermore, there was little evidence of an intermediate increase in yield, suggesting that a) ecosystem services do not strongly depend on distance or b) their effect is relatively small. This study represents one of the first uses of precision yield data to measure ecosystem service provision at large spatial scales.

<sup>6</sup> **Keywords:** precision yield; spillover; landscape;

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<sup>7</sup> Potential journals: Agriculture Ecosystems and Environment, Basic and Applied Ecology, Ecological  
<sup>8</sup> Economics, Journal of Applied Ecology (probably won't like it)

<sup>9</sup> Potential reviewers: Teja Tscharntke, Ignasi Bartomeus, Ben Woodcock, John Redhead, some  
<sup>10</sup> Canadian/Albertan reviewers who know the crop systems?

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11    **1. Introduction**

12       Intensive agricultural production has increased over the last 100 years, and agricultural land now  
13      makes up over a third of ice-free land on Earth. This has allowed increases in human population  
14      and increased global stability in production. However, this is not without cost, as higher-diversity  
15      non-crops are converted to lower-diversity crops, resulting in loss of habitat and overall biodiversity of  
16      non-target organisms. Maintaining both biodiversity and production in agroecosystems represents a  
17      goal of conservationists and agronomists, and holds the potential for win-win scenarios.

18       Key to this goal is the preservation of semi-natural land (SNL) in and around crops, which represents  
19      the interface between crops and non-crops within agroecosystems. SNL in agroecosystems is important  
20      for both agricultural production and conservation (Prieto-Benítez & Méndez 2011), and can create  
21      better biotic and abiotic conditions for crop growth (Case *et al.* 2019; Weninger *et al.* 2021; but see  
22      Lowe *et al.* 2021). SNL constitutes habitat for mobile organisms, and can act as sources of ecosystem  
23      services such as pollination or pest control (Albrecht *et al.* 2020; Gardner *et al.* 2021), but this can vary  
24      depending on the system (Gray & Lewis 2014; Quinn *et al.* 2017). They also can create microclimate  
25      effects that reduce extreme temperature, trap moisture, and reduce wind speed (Kort 1988; Brandle *et*  
26      *al.* 2004). North American agroecosystems have larger fields, different crop varieties, and agronomic  
27      practices, all of which could negate or confound potential effects of SNL.

28       SNL may affect yields at intermediate distances, depending on the spatial scale at which ecosystem  
29      services operate. Edge effects cause low yields at the edge of crops because of sparse or late seedling  
30      emergence, poor microclimate, and competition with weeds. At the same time, the centre of large  
31      fields will not receive ecosystem services if they decay with distance from edges (Kowalchuk & Jong  
32      1995). For example, pollination services from central place foragers (bees) that nest in SNL but forage  
33      in crops drops rapidly with distance (Garibaldi *et al.* 2011). Therefore, yield may be maximized at  
34      intermediate distances, where the ecosystem services cancel out negative edge effects [Van Vooren *et al.*  
35      (2017); Figure 1]. This also suggests a “goldilocks” field size, where negative edge effects are canceled  
36      out by ecosystem services.

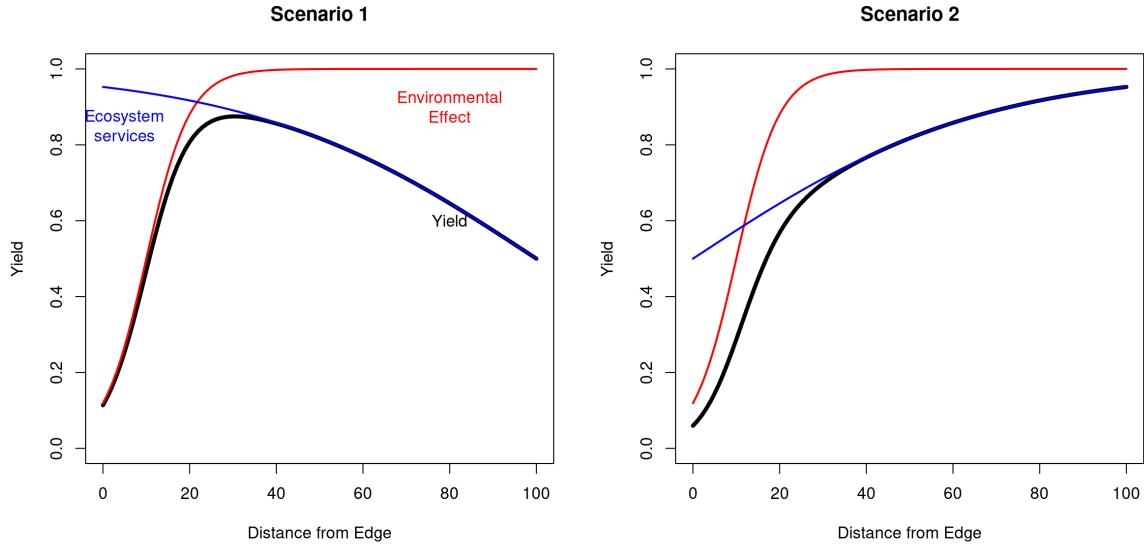


Figure 1: Potential yield patterns, depending on ecosystem service effects with distance. In both figures, negative environmental effects (edge effects) are shown in red, and decrease with distance from the edge of the crop, creating an increase in yield with distance. The left figure shows a decline in ecosystem services with distance, leading to an intermediate peak in yield, while the right figure shows an increase in services with distance, leading to a peak at the centre of the field (note: Scenario 2 also occurs if ecosystem services do not change with distance).

Studies of SNL effects on crop yield also suffer from limited scope (e.g. few crop types) and small sample sizes, limiting inference and reducing generality (Baker *et al.* 2018; but see also Redhead *et al.* 2020). Meta-analyses have been the standard solution to this problem (e.g. Albrecht *et al.* 2020; Lowe *et al.* 2021), but precision yield data holds enormous promise because of its common usage and relatively cheap operating costs. However, its use is limited for several reasons, namely: 1) Lack of standardized formats between equipment types, 2) Sensor calibration required for field-level accuracy, and 3) low familiarity with spatial statistics. Ecosystem services can influence both the mean and variability of yield in agroecosystems (Redhead *et al.* 2020); typically only averages (means) are considered, but higher stability (lower variance) in yield can also be valuable from a grower's perspective. There are few studies of yield variability (only those with large datasets), but precision yield data opens up the possibility of modeling within-field variability, as well as average yield.

In this paper we ask: 1. How does crop yield change with distance from the edge of field? 2. Does this depend on type of field edge? 3. Is there an intermediate distance where yield is maximized or variance is minimized? To our knowledge, no other study has addressed the effect of field boundaries on productivity using precision yield, making this study highly novel.

52    **2. Methods**

53    *2.1. Data collection*

54       Precision yield data were collected directly from farmers across Alberta. Farmers were solicited for  
55       yield data through local agronomists, and we received 298 field-years of data from 5 growers across  
56       a total of 7 years (2014-2020). We converted raw data to a standard csv format using Ag Leader  
57       SMS. 85% of the crop types where either wheat (*Triticum aestivum*), canola (*Brassica napus*), or peas  
58       (*Pisum sativum*), three of the most common crops in rotation in Alberta (Statistics Canada 2014). The  
59       remaining crop types had low replication, so we constrained our analysis to only field-years containing  
60       wheat (94), canola (119), or peas (39), for a total of 252 field-years of data. Individual fields contained  
61       between 1 and 6 years of data (mean: 3.1), containing a total of 14.4 million data points.

62       Yield data was collected in rectangles of the same length as the data interval (distance = combine  
63       ground speed  $\times$  interval, typically 1 second) and the same width as the combine header (5-7 m, adjusted  
64       to account for overlap with adjacent swaths). We extracted the size of each polygon ( $m^2$ ), dry yield  
65       (tonnes), and the spatial location, and the sequence of collection (1 - end of harvest) Because of the  
66       large number of yield rectangles per field (30-800 thousand), we used the centroid of each polygon as  
67       its location, treating areal data as point data Seeding and application rates were constant across fields,  
68       so we did not consider inputs in our analysis We used dry yield (tonnes of seed/hectare minus recorded  
69       crop moisture) as our measure of crop yield Precision yield data can be highly variable and is prone to  
70       extreme outliers (both positive and negative), especially when combine ground speeds are low and at  
71       the beginning of rows Therefore, we filtered data that lay outside the 95th percentiles of yield within  
72       each field, values less than or equal to zero, and values outside of the 95th percentiles of ground speed.  
73       Due to the large number of data at each field, we sub-sampled to 50,000 data points per field to reduce  
74       computation time.

75       Field boundaries were automatically digitized using buffers from the yield data locations, then  
76       manually checked using satellite imagery from Google Earth and classified land cover data from AAFC.  
77       Crop boundaries are flexible, and often change yearly depending on planting and emergence conditions  
78       (e.g. flooding during some years). Ephemeral wetlands are flooded during some years, but consist  
79       mainly of grasses during dry years, and grass boundaries can change if fields are used for as haying  
80       or pasture during crop rotation. This makes accurate and consistent classification of field boundaries  
81       difficult. We defined the following general categories for field boundaries: 1. Standard: grassy field edge,  
82       staging yard, or road right-of-way (grassy strip typically 5-10m wide) 2. Wetland: permanent wetland;

83 borders are largely unchanged from year-to-year  
 84 3. Shelterbelt: permanent windbreaks, shelterbelts,  
 85 remnant forests, or shrublands  
 86 4. Other crop: annual crop or pasture with little or no visible boundary  
 87 between planted areas  
 88 5. Bare: unplanted, fallow, flooded area, temporary wetland (only present for a  
 89 single season), staging yard, oil and gas equipment, or road without a planted boundary  
 90 6. Grassland:  
 91 permanent seminatural grassland or pasture (not in rotation)

92 *2.2. Analysis*

93 Yield data from each field contains both random and systematic errors that must be modeled in  
 94 order to reveal underlying changes in yield. We fit an additive model of the effect of boundary distance  
 95 on crop yield while accounting for within-field spatial variation and temporal variation in the data.  
 96 Crop yield can vary within a field due to soil conditions, moisture, seeding rates, herbicide application,  
 97 and previous agricultural practices. Ground speed is extremely important to yield monitor accuracy  
 98 (Arslan & Colvin 2002), with low ground speed registering higher yields. Sensor calibration can reduce  
 99 combine-level bias (such as a combine recording consistently higher/lower yields across fields), this does  
 100 not address sensor drift that occurs over time. This may be caused by sensors accumulating debris  
 101 during harvest (pers. comm. Trent Clark), leading to changes in accuracy and bias over time. To  
 102 model this, we fit the following model to each field-year of data:

$$\sqrt{yield} \sim Normal(\mu, \sigma)$$

$$\begin{aligned}
 \mu = & Intercept + log(Polygon\ Size) + f(Edge\ Distance, b = 12)_i + \\
 & f(Easting, Northing, b = 60) + f(Sequence, b = 60) \\
 log(\sigma) = & Intercept + log(Polygon\ Size) + f(Edge\ Distance, b = 12)_i + \\
 & f(Easting, Northing, b = 60) + f(Sequence, b = 60)
 \end{aligned} \tag{1}$$

- 103 • where:  
 104
1. Polygon Size = distance traveled  $\times$  width of header bar ( $m^2$ )
  2. Edge Distance = distance from field edge type  $i$  (m)
  3. Easting, Northing = distance from centre of field (m)
  4. Sequence = order of harvest within field (1–N points)
  5.  $f(x,b)$  = penalized thin-plate regression spline, where  $x$  is the predictor and  $b$  is the number of  
 105 basis dimensions

106 In addition to modeling edge effects (our variable of interest), this model also accounts for a)  
107 differences in harvested area, b) within-field spatial variation not related to edges, and d) shifts in  
108 combine accuracy during harvest. Spatial or temporal variation can be modelled using a Gaussian  
109 Process Model (e.g. Kriging, SPDE Approximations) but this was computationally unfeasible with  
110 50,000 data points per field. Penalized splines offer a compromise, as they account for nonlinear “wiggly”  
111 relationships in the same way as Gaussian processes but using a reduced number of dimensions and  
112 computation time. The number of basis dimensions was checked with the *gam.check* function from  
113 *mgcv*. The relationship between polygon size and yield was modeled with a log-linear relationship with  
114 a single slope term, as this closely matched smoothed versions. Because polygon size is not intuitive,  
115 we converted it into ground speed by regressing speed on distance traveled per polygon, then using this  
116 to back-calculate the ground speed for a given polygon size (given a fixed width of header). All models  
117 were fit in *R* using the *mgcv* library (version 1.8.36, Wood 2017), and figures were created with *ggplot2*  
118 and *ggpubr* (versions 3.3.3, Wickham 2016; and 0.4.0, Kassambara 2020).

119 Despite the use of spatial and temporal smoothers, the residuals in most of the models displayed a  
120 large amount of spatial and temporal autocorrelation. *Not really sure how we can get around this. In*  
121 *practice, this means that SEs for all coefficients are too small (i.e. we gathered 1000 points, but because*  
122 *they’re spatially related, it’s only equivalent to 100 points).*

123 To consider results from all field-level models together, we fit models independent of each other and  
124 fit an “overall” smoother as averages of the field-level smoothers. However, this does not account for  
125 uncertainty in the field-level smoothers, so we used an approach similar to bootstrapping of hierarchical  
126 mixed effects models: 1. Extract single posterior sample (*rnorm* in R) of smoother parameters from  
127 each field-level model using coefficient estimates and standard error 2. Use posterior sample to create  
128 a new smoother from each field 3. Fit new model of new smoothers from all fields, and save this  
129 “meta-smoother” 4. Repeat 1000 times, and calculate coverage intervals (5-95% percentiles) on saved  
130 meta-smoothers This gives coverage intervals (CIs) for the “average” smoother while accounting for  
131 field-level variability, and is conceptually similar to a meta-analysis. Spatial variability was not averaged  
132 between fields because differences in field geometry make it impossible to compare fields.

133 **3. Results**

134 *3.1. Field-level example*

135 The filtered data from each field still contained a large amount of variation, but the non-stationary  
136 additive models were able to reveal underlying yield patterns. To illustrate this, we show the results from  
137 a single wheat field, where we show the relative impact of ground speed, harvest sequence, boundary  
138 distance, and spatial variation on both yield mean and yield SD (“patchiness”). Figure 2 shows the raw  
139 data collected from a single field, demonstrating a large amount of variation even among the filtered  
140 data. Combine ground speed had a large effect on both yield mean and SD, and there was also a strong  
141 effect of harvest sequence on yield mean and SD (Figure 3. Yield mean and SD tended to decrease with  
142 distance from field boundaries, but there were no consistent differences between boundary types (Figure  
143 4. Finally, the random spatial smoothers in Figure 5 show that yield mean and SD systematically vary  
144 within fields, likely due to moisture, elevation, or soil conditions (Figure 5.

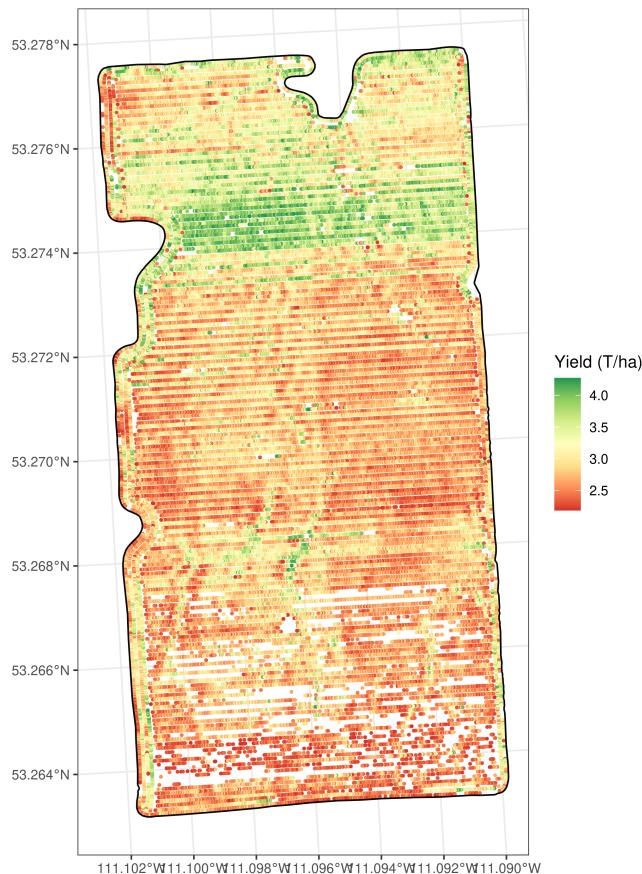


Figure 2: Example output from a single field.

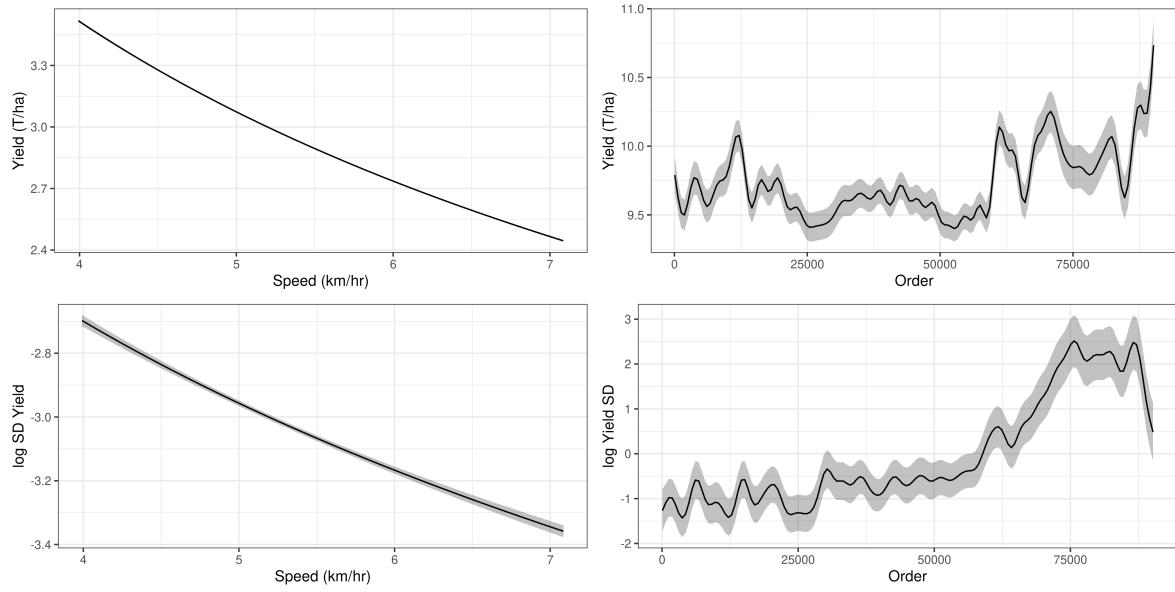


Figure 3: Ground speed and harvest sequence (random temporal variation) smoothers from a single field.

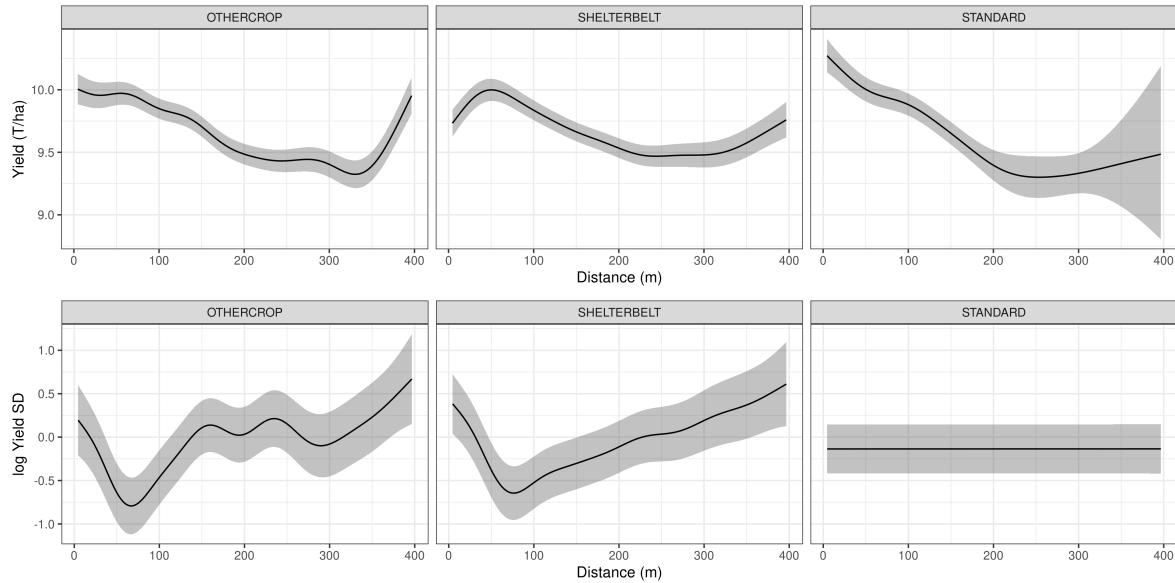


Figure 4: Distance smoothers from a single field.

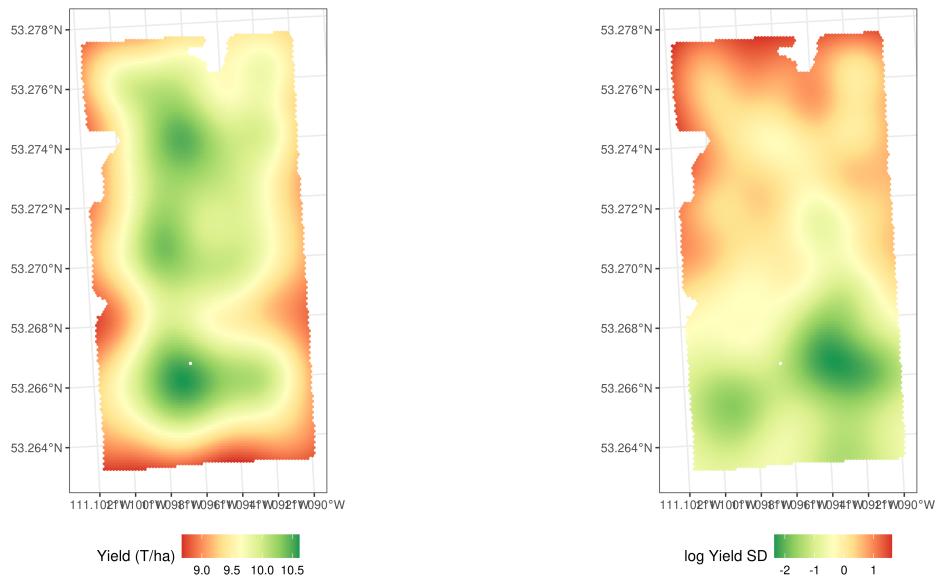


Figure 5: Spatial (random spatial variation) smoothers from a single field.

145     3.2. Overall results

146       Across all fields, Standard (grassy border) field boundaries were the most common boundary type,  
 147       followed by Shelterbelts and Other Crops (Figure 6).

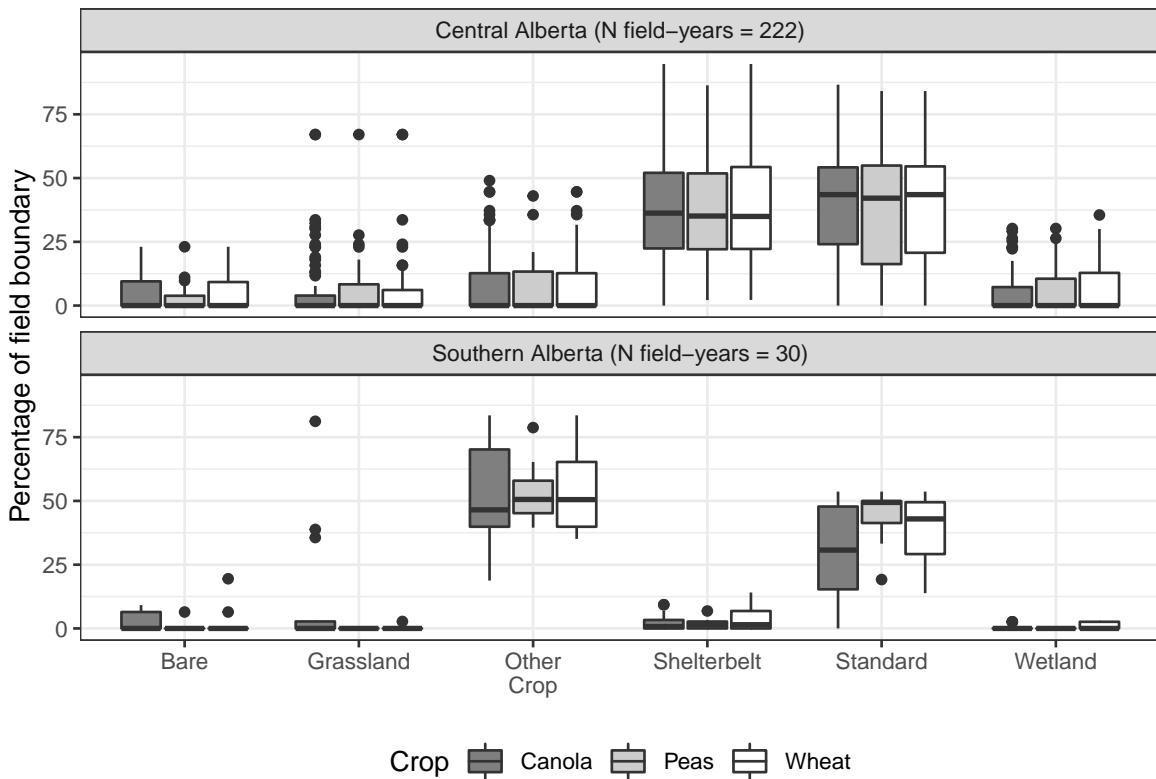


Figure 6: Percentage of field boundaries across sampled fields.

148    3.2.1. *Canola fields*

149    Overall, there was a strong negative effect of combine ground speed on both the average and  
 150    variability of canola yield. At the field level, both yield average and yield variability (SD of yield) of  
 151    yield were extremely spatially (average p-values: 2e-16, 1.77e-05) and temporally dependent (2e-16,  
 152    0.000243), meaning that average and variability changed with location in the field, as well as sequentially  
 153    during the harvest. However, there was no difference in average or variability with harvest sequence  
 154    when all fields were considered, meaning that combines did not appear to distort yield data from start  
 155    to finish in any systematic way.

156    Average canola yield tended to increase with distance from Standard and Other Crop boundaries,  
 157    leveling off at about 25 m (Figure 7 top row, Other crop and Standard panels); yield was approximately  
 158    0.1 T/ha (1.5 bu/ac) lower at the edge for both of these boundary types. Interestingly, Shelterbelts  
 159    were well-represented in the data (Figure 6) but the negative edge effect was not strong (Figure 7 top  
 160    row, Shelterbelt panel), indicating that they may provide better micro-climates for crops located near

them. Other boundary types were less common in the data and had correspondingly weaker effects on mean yield, but all showed a small negative edge effect. Yield variability tended to decrease with distance from the edge of the field, indicating that edge effects contribute to yield “patchiness” as well as averages. At Standard, Bare, and Wetland field boundaries, variability decreased until about 100 m, after which variability was constant, while the pattern was less consistent in Grassland, Other Crop, and Shelterbelt.

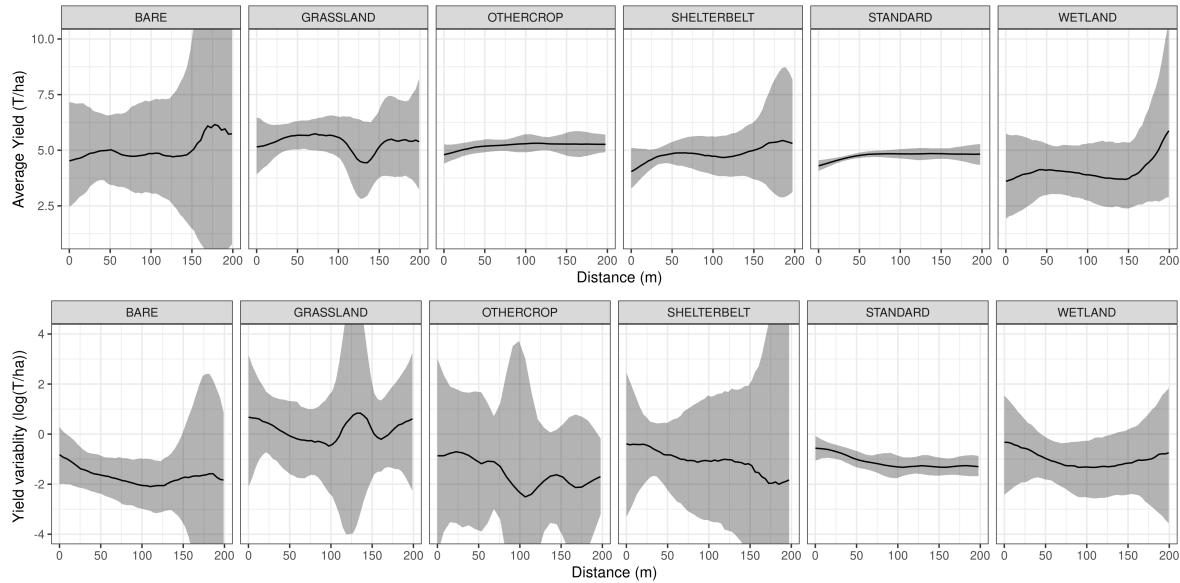


Figure 7: Field boundary effect on canola yield, accounting for the effect of combine speed, spatial variation, and harvest sequence. Upper panel represents mean yield, while the lower panel represents yield variation (i.e. “patchiness”).

### 167 3.2.2. Wheat fields

168 Similar to canola, there was a strong negative effect of ground speed on both yield and variability  
169 of wheat yield (Figure 11, left panels). At the field level, both yield average and yield variability (SD of  
170 yield) of yield were spatially (average p-values: 2e-16, 2e-16) and temporally dependent (2e-16, 2e-16),  
171 but harvest sequence did not distort the average or SD of wheat yield in a systematic way (Figure 11,  
172 right panel).

173 Average wheat yield increased slightly with distance from the field boundary, but this was much  
174 more variable than the patterns seen in canola yield (Figure 8). There was also a slight increase in  
175 variability away from the field boundary, at least for Standard and Other Crop boundaries, but this  
176 was inconsistent among other boundary types.

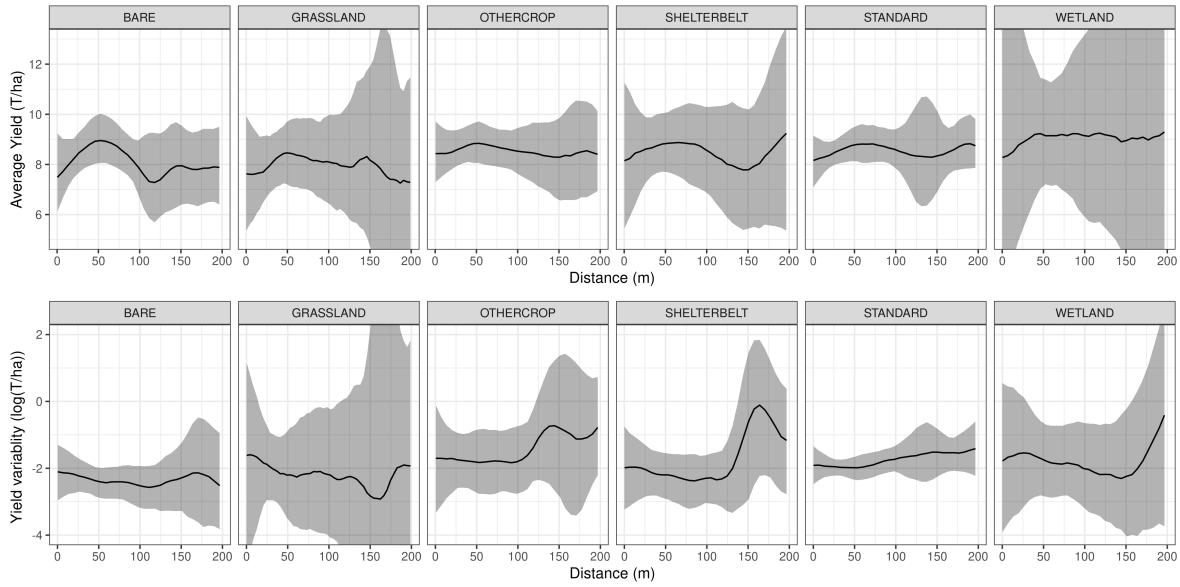


Figure 8: Field boundary effect on wheat yield, accounting for the effect of combine speed, spatial variation, and harvest sequence. Upper panel represents mean yield, while the lower panel represents yield variation (i.e. "patchiness").

<sup>177</sup> *3.2.3. Pea fields*

<sup>178</sup> At the field level, both yield average and yield variability (SD of yield) of yield were spatially  
<sup>179</sup> average p-values: 2e-16, 2e-16) and temporally dependent (2e-16, 3.62e-07), There was a strong negative  
<sup>180</sup> effect of ground speed on yield and variability of peas (Figure 12), but harvest sequence did not distort  
<sup>181</sup> the average or SD of wheat yield in a systematic way (Figure 12, right panel).

<sup>182</sup> Average pea yields increased with distance from Shelterbelt, Standard, and Wetland field boundaries.  
<sup>183</sup> Interestingly, the reduction at the edge was slightly higher for Wetlands, but yield increased with  
<sup>184</sup> distance more quickly, i.e. yields were higher at distance for Wetlands. Yield variability decreased  
<sup>185</sup> with distance from Grassland and Standard boundaries, and was slightly lower overall at Standard  
<sup>186</sup> boundaries.

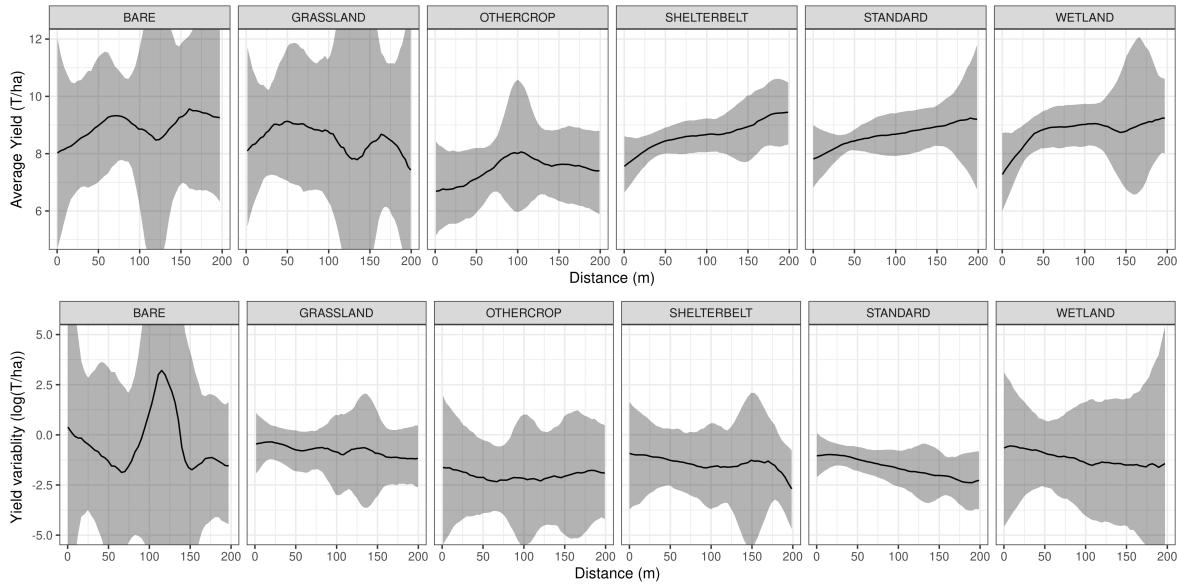


Figure 9: Field boundary effect on pea yield, accounting for the effect of combine speed, spatial variation, and harvest sequence. Upper panel represents mean yield, while the lower panel represents yield variation (i.e. "patchiness").

#### 187 4. Discussion

188 At the level of individual fields, both average and SD of yield varied with distance from the field  
 189 boundary. Both metrics also varied with ground speed and harvest sequence, and there were strong  
 190 spatial relationships within each field, likely related to underlying soil or moisture conditions. Yield  
 191 tended to increase with distance from field boundaries before plateauing, but there was little evidence  
 192 of intermediate boosts in yield, meaning that ecosystem services likely increased or did not vary with  
 193 distance from field boundaries (Scenario 2, Figure 1). Some crops displayed a larger decrease in yield  
 194 next to field boundaries; for example, pea yield directly adjacent to Wetland was lower overall, but  
 195 increased with distance more than other crop types, indicating that Wetlands may locally decrease  
 196 pea yields but are beneficial to the crop in general. Canola yields next to Other Crops had a reduced  
 197 edge effect compared to Standard field boundaries, indicating that Other Crops may provide a more  
 198 consistent microclimate for canola than grassy field boundaries. However, the difference between  
 199 boundary types tended to be both small and variable, especially for wheat.

200 Why did we find few consistent effects of boundary type on crop yield? We consider a few potential  
 201 reasons for this below: 1. Landscape influence 2. Boundary variables 3. Ecosystem disservices 4.  
 202 Yearly/location variation 5. Lack of pest pressure/pollination deficit

203 Our analysis only examined boundary types, without considering the landscape context that fields  
204 were embedded in. Some studies show the influence of landscape composition at larger spatial scales  
205 (e.g. Lan's paper) which could be particularly important when beneficial arthropods are highly mobile  
206 (e.g. bumblebee foraging) or disperse very broadly (Öberg *et al.* 2007). There could also be interactions  
207 between landscape composition at different scales (Motzke *et al.* 2016; Robinson *et al.* 2021), but this  
208 is not well-studied. Landscape complexity (Fahrig *et al.* 2011) and connectivity are also associated  
209 with higher abundance of beneficial arthropods (Paul's new paper + others). This means that field  
210 boundaries such as wetlands or shelterbelts may only be helpful if connected to a larger network of  
211 non-crop habitat (but see Fahrig *et al.* 2019). Our definitions of boundary type were also (necessarily)  
212 loose, as we used satellite imagery to manually classify them. However, it may be that other boundary  
213 traits, such as size or plant species composition, are more important for spillover of ecosystems services  
214 into fields. For example, larger (Lecq *et al.* 2018; Stašiov *et al.* 2020) or more functionally diverse  
215 (Bonifacio *et al.* 2011; Boughey *et al.* 2011) hedgerows tend to support more biodiversity than smaller  
216 hedgerows, and some studies have shown that leaf litter and soil compaction matters to predatory beetle  
217 communities (Sutter *et al.* 2018). These fine-scale boundary characteristics were not measured in our  
218 study, but could be used as variables in more biologically-meaningful classifications of field boundaries.

219 Our first scenario (Scenario 1, Figure 1) assumes that beneficial organisms disperse from boundaries  
220 into the field, and had a generally positive effect on crop yield. However, field boundaries may not have  
221 a positive effect if a) pests (ecosystem dis-services) also disperse along with beneficials, b) if beneficials  
222 do not disperse from the boundary environment, or if c) the effect of beneficial organisms is small.  
223 Ecosystem disservices such as pests and weeds can also disperse from field boundaries, which may  
224 negate any positive effect of ecosystem services (Zhang *et al.* 2007). Gray & Lewis (2014) showed that  
225 remnant forest fragments do not provide significant pest control services , but also do not depress yield.  
226 However, this is still poorly studied, and parsing out services from disservices is impossible using crop  
227 yield data *alone*. Ecosystem services from field boundaries may be limited if beneficial organisms stay  
228 in field boundaries, or disperse at wider spatial scales Robinson *et al.* (2021). Finally, pest pressure or  
229 pollination deficit may be low enough that ecosystem service provision does not significantly change  
230 yield. Canola is largely self-pollinating (at least in hybrid canola varieties, Lindström *et al.* 2016) and  
231 wheat is wind-pollinated, meaning that slight increases in pollination services may not change yields  
232 significantly in either crop (Woodcock *et al.* 2016). Pests are also limited by growers' application of  
233 insecticides (seed-treated or on the crop directly), and insect pest outbreaks tend to be temporally and

234 spatially spotty.

235 Since our sampling represents a limited amount of spatial and temporal coverage, there could be  
236 additional confounding variables that obscure signals of yield. Most fields were located in Central  
237 Alberta (Dry Mixedwood region, Natural Regions Committee 2006), where boundaries contained a  
238 higher proportion of Shelterbelts (Figure 6), but differences from Southern AB (Foothills Fescue and  
239 Mixedgrass region) may be confounding the signal. Between-year effects may be important, especially  
240 during dry years (Kort 1988), but this was not considered in our analysis. Future work could examine  
241 whether boundaries have differing effects during hot or cool years.

242 We used harvest time as smoothed variable to deal with temporal autocorrelation in the data, but  
243 this is a crude way to deal with this. This is because in-field combine driving patterns *almost always*  
244 induce correlation between spatial and temporal measurements (e.g. northern section of the field was  
245 harvested before the southern section), meaning that temporal and spatial random effects are difficult  
246 to separate. There are few solutions to this using harvest data as-is, other than to ignore temporal  
247 random effects entirely, thereby constraining all random variation to be spatial. However, it is possible  
248 to remove correlation between spatial and temporal measurements by using specially designed harvest  
249 patterns within a field (harvesting alternating strips sequentially across the field, then harvesting the  
250 remaining strips on a second pass). Future studies could use this to estimate drift in combine sensor  
251 measurements over time.

## 252 **5. Author Contributions**

253 SVJR and PG conceived of the project. SVJR collected data, conducted analysis, and wrote the  
254 manuscript.

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350 Appendix A: Supplementary Material

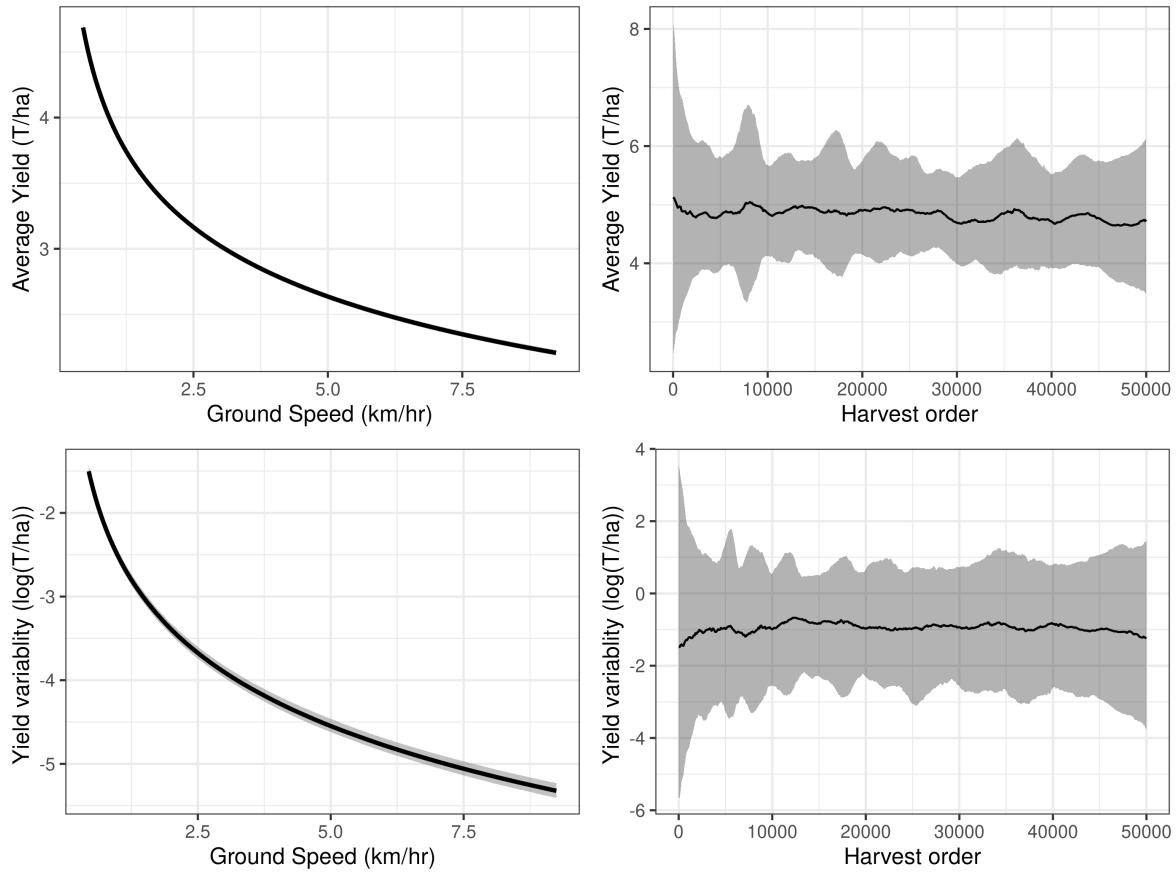


Figure 10: Effect of ground speed and order (sequence of harvest) on canola yield.

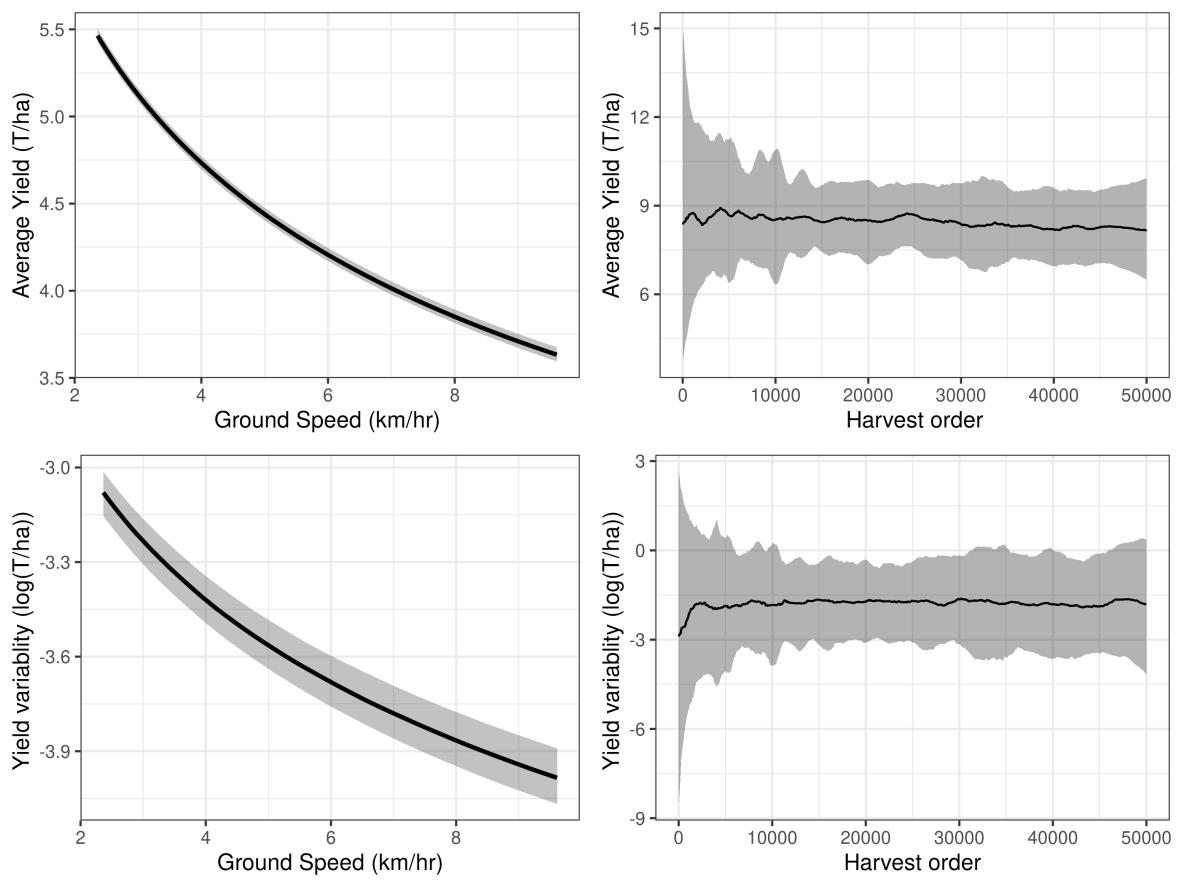


Figure 11: Effect of ground speed and order (sequence of harvest) on wheat yield.

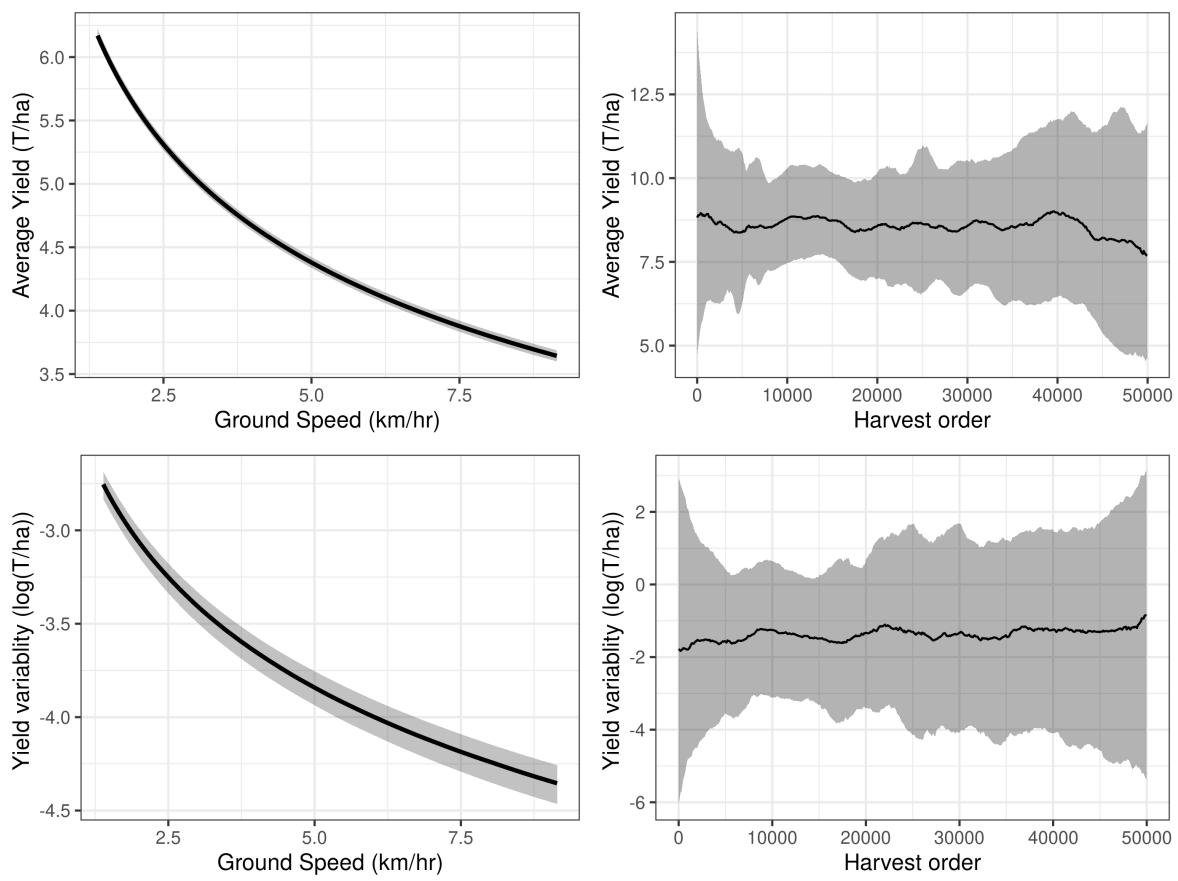


Figure 12: Effect of ground speed and order (sequence of harvest) on pea yield.