Landscape complexity effects on crop productivity: an assessment from space

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Abstract

In the agricultural landscape of south-central Alberta, Canada, producers have many incentives to clear small natural habitats from their fields, as this can expand their cultivated land base and reduce time taken to steer equipment around those areas. However, those natural habitats can provide shelter and food for beneficial arthropods which provide ecosystem services to agriculture, such as pollination or natural pest control. Here we assessed the impact of marginal habitats on adjacent canola (*Brassica napus*) fields at both the field-level and the subfield-level using remote sensing data by measuring the "landscape complexity," the amount and arrangement of both crop and non-crop covers surrounding a canola field. At the field-level, canola fields with higher landscape complexity generally had higher mean yields. However, fields surrounded mostly by crop or non-crop covers had lower yields, possibly due to a lack of pollination or natural pest control services or an overwhelming yield-reducing edge effect. At the subfield-level, we found evidence of a boost in yield between 30 and 100 meters from the field edge towards its center. There is also a plausible yield stabilizing effect at the same range.

Keywords: landscape complexity, canola, remote sensing, precision agriculture, conservation

1. Introduction

The Canadian prairies are now one of the world's most endangered ecosystems, as at least 70% of native grasslands have been lost due to development and conversion to agriculture (*AEP, 1997*). In addition to grasslands, about 70% of wetlands have been removed or altered since European settlement (*DUC, 2006*). Drainage constitutes approximately 84% of these losses, as the region has had a long history of installing ditches that drain water from wetlands so more land can be farmed (*NAWMP, 2020*). The loss of wetlands and grasslands comes with the loss of their beneficial ecosystem services to both people and natural systems. Some of these services include providing habitat for wildlife, maintaining soil or water quality, regulating water resources, and storing carbon (*Zedler & Kercher, 2005; Mitsch et al., 2013; Conant et al., 2017; Bengtsson et al., 2019; Xu et al., 2020; Zhao et al., 2020*).

In the agricultural landscape of south-central Alberta, wetlands and other non-crop spaces — such as field margins, fencerows, shelterbelts, and tree patches — are common throughout the region. Producers have many incentives to clear small natural habitats from their fields, as this can expand their cultivated land base and reduce time taken to steer equipment around those areas. However, producers are also concerned with the sustainable crop production as well as public trust in their enterprise and are interested in approaches that avoid additional land conversion. Ecosystem services could further incentivize producers to retain semi-natural areas, as crop production has been shown to benefit from non-crop spaces such as field margin habitats (*Blaauw & Isaacs, 2014; Tschumi et al., 2016; Venturini et al., 2017; Rundlöf et al., 2018*). Non-crop spaces can provide shelter and food for beneficial arthropods (*Garibaldi et al., 2014; Venturini et al., 2017; Vickruck et al., 2019*), even in intensively farmed areas (*Morandin et al., 2014*). In many cases, those arthropods (e.g., bees, wasps, flies, spiders, beetles) provide ecosystem services to agriculture, such as pollination or natural pest control, which may help to improve yields, decrease inputs, and increase overall profitability (*Albrecht et al., 2020*).

In general, there is a positive relationship between the diversity and abundance of beneficial species and landscape complexity (the amount and land cover diversity of the non-crop spaces) (*Klejin et al., 2019; Zamorano et al., 2020*). However, the relationship between landscape complexity and crop yield—the main concerns of producers—is not well studied. In addition, what is known about this relationship is either based on small-scale field studies (*Tschumi et al., 2016; Rundlöf et al., 2018*) or regional analyses (*Galpern et al., 2020; Nelson & Burchfield, 2021*). Existing regional analyses, e.g., using county-level yield data, cannot include sufficient field-level detail to support predictions relevant to individual producers, while field studies can be labour-intensive and are often limited to a few fields and/or years (limiting their generality and applicability). However, adoption of precision agriculture and remote sensing technologies has the potential to change this. Precision agriculture has been practiced commercially since the 1990s (*Mulla, 2013*) and is now deployed widely across the North American agricultural sector. In Canada, 84% of producers are currently using combine yield monitoring capability which allows them to obtain much information about their fields, such as grain yield and moisture content (*Steele, 2017*). Recent work has demonstrated that it is possible to reliably predict crop yield based on its relationship with remote sensing imagery where field-level precision agricultural data is not available (*Hunt et al., 2019; Nguyen et al., 2021*). Therefore, maps of crop yield, either directly based on field data or predicted from remotely sensed data, can be potential alternatives to plot-based field sampling, and present a new method of assessing the influence of landscape complexity of marginal habitats (and therefore, the strength of ecosystem services) on crop productivity.

Our objective in this study is to assess potential impacts of marginal habitats on adjacent canola field using remote sensing products. We hypothesized that (1) non-crop spaces at the field edge—including both outer and inner edges—that host arthropods that provide ecosystem services to canola will create a boost to yield and therefore that (2) fields with higher landscape complexity, and consequently greater interface between natural habitats and the crops, would have a higher average yield.

To test the first hypothesis, we first mapped precision canola yield and field boundaries using Sentinel-2 time series. Next, distance-to-the-nearest-edge were computed for every pixel on the field. Potential effects of non-crop spaces on canola yield were then modelled as the nonlinear relationship between subfield-level yield and distance-to-the-nearest-edge. To test the second hypothesis, we first described landscape complexity of each canola field by counting numbers of non-crop and crop pixels surrounding the field within various disks (normalized by each field's area). Then, for each disk, field-level yield was modelled as a function of the interaction between crop and non-crop edges. This study is among very few studies assessing roles of field marginal habitats and crop production and is the first, to our knowledge, to utilize remote sensing products to do so.

2. Materials and Methods

2.1. Study Area & Data

This study covers a 100×100 km area centered around eight canola fields in the County of Vermilion River (Alberta, Canada) where a 2019 precision yield dataset was available to build a yield mapping model (Figure 1). Precision yield data was recorded in segments by the combine's on-board yield monitor. Each segment is characterized by a starting position of the combine, width of the header bar (m), direction of travel (0-360° N), the length of a recorded segment (m), and the canola yield (dry mass in tonnes/ha). We used those attributes to construct harvested segments (polygons) and rasterized those polygons to create yield maps that spatially match with Sentinel-2 pixels at 10-meter resolution (*Nguyen et al., 2021*, Figure 2c).

Sentinel-2 is a European wide-swath, high-resolution, multi-spectral imaging mission designed with twin satellites to give a high revisit frequency (5 days at the Equator). Each satellite carries a Multi Spectral Instrument (MSI) payload that samples 13 spectral bands: four bands at 10-meter (including Red, Green, Blue and NIR), six bands at 20-meter, and three bands at 60-meter spatial resolution. In this study, 2019 Sentinel-2 MSI L1C scenes (top-of-atmosphere reflectance product) were downloaded from the Copernicus Open Access Hub. We then used the SNAP v7.0.0 software (ESA Sentinel Application Platform) to generate the bottom-of-atmosphere reflectance product (L2A). The generation of L2A also returned a Scene Classification (SCL) map which was used to filter "bad" pixels (cloud/cloud shadow, snow, and ice). The remaining good observations in each band were stacked to create a time series dataset at each pixel. Here we used Sentinel-2 time series of the Apr-01-2019 to Oct-31-2019 period to map canola field boundaries and to build a functional regression model for mapping canola yield at 10-meter resolution.

2.2. Mapping Land Covers and Canola Field Boundaries

We generated a land cover map of the study area (7 classes: water, wetland, grass/shrub, forest, barren/urban, canola, and other crops) at 10-meter spatial resolution using statistical features generated from Sentinel-2 time series and Random Forest classifier (*Nguyen & Henebry, 2019*). The sample data pool (for training and testing) was manually created based on the Annual Crop Inventory (ACI, at 30-meter resolution; *AAFC, 2019*) due to its high accuracy level for crop categories. The classification was repeated 100 times, and then aggregated to create a final map by selecting the most popular cover at each pixel. Each time, training and testing datasets were randomly drawn from the sample data pool. The average overall accuracy is 90%, and average producer's/user's accuracy are both greater than 95% for canola. After classification, we only kept canola patches between 20 and 120 hectares as a typical canola field in the study region is between 1 and 2 quarter sections (a quarter section is approximately 64 hectares). Retained fields were then visually inspected and edited, using the World Imagery Basemap available in ArcGIS software—a very high-resolution image updated typically within 3-5 years of present—and the Sentinel-2 natural composite images, to make sure that canola field boundaries were detected accurately. In total, 757 canola fields were identified within the study area for further analysis (Figure 1). At each field, we computed distance from any canola pixel to its nearest edge.

2.3. Mapping Precision Canola Yield

From spectral bands, two spectral indices were computed: normalized difference vegetation index (NDVI; *Huete et al., 1997*) and normalized difference water index (NDWI; *Gao, 1996*). We modeled the rasterized canola yield as a function of NDVI and NDWI time series (Equation 1) in R using the "fda.usc" package (*Febbraro & Oviedo de la Fuente, 2012*). This functional regression model can predict canola yield to within 12-16% accuracy of actual yield, and to capture within-field variation (*Nguyen et al., 2021 Preprint*; Figure 2). We then used the model to map precision canola yield for all studied fields.

A functional linear regression (FLR) models crop yield, *y*, as:

$$y = f(X, \beta) + \varepsilon = \int X(t)\beta(t)dt + \varepsilon \qquad [1]$$

where X is the value of predictor variables at time t (NDVI and NDWI, in our case), while β is the instantaneous effect (slope) of that variable on y. One way of estimating β is to present the parameters (β) and the functional covariates (X_i) as a finite sum of pre-defined basis elements:

$\beta(t) = \sum_k \beta_k \theta_k(t) = \theta' b$; $X_i(t) = \sum_k c_{i,k} \psi_k(t) = C\Psi$. Replacing β and X of equation 1 by their new forms results in equation 2—a typical multiple linear regression.

$$y = f(X, \beta) + \varepsilon = C\Psi\theta' b + \varepsilon = Zb + \varepsilon \quad [2]$$

2.4 Effects of field edge on subfield-level mean and variance of canola yield

Here we assessed the impact of field edge (i.e., non-crop spaces at field boundary that separate a field from surrounding non-crop covers or other crop fields) on subfield-level canola productivity using two different approaches. First, we used an empirical "bin-yield" approach, based only on simple descriptive statistics, making it suitable for a large-scale analysis of the field edge impacts (regional to national scale). Secondly, we modeled the non-linear relationship between pixel-level yield and proximity to the field boundary using additive models.

(a) Empirical "bin-yield" analysis

At each field, we separated canola pixels into 10-meter distance bins according to their distance-to-the-nearest-edge and computed descriptive statistics of canola yield (mean and variance) for each bin. Using this binned dataset, impacts of field edge on subfield-level canola productivity was then presented by mean and standard deviation values of "mean bin-yields" and "variance bin-yields" across all distance-to-the-nearest-edge bins.

(b) Non-linear modeling analysis

For each canola field, we modeled the relationship between yield and distance to the nearest edge using a Generalized Additive Model (GAM) provided by the "mgcv" package in R (*Wood, 2017*). In a GAM, linear terms are replaced by non-parametric smooth functions of covariates and can model nonlinear relationship between predictors and response variables. The structure of GAM can be written as:

$$g\big(E(Y)\big) = \beta + s_1(X_1) + s_2(X_2) + \cdots + s_n(X_n) \quad [3]$$

where *g(E(Y))* is the link function that links the expected value of the response variable, *Y* to the basis functions used to represent predictor variables $(X_1, X_2, \ldots, X_n)$. The terms $s_1(X_1)$, $s_2(X_2)$, …, $s_n(X_n)$ denote non-parametric smooth functions. In this study, a Gaussian location-scale GAM was used to model mean and variance of yield simultaneously. We modeled mean and variance of yield as functions of distance to the nearest edge and included a two-dimensional spatial smooth (Equations 4 & 5, family *gaulss* in *mgcv*). Spatial smoothers were used to account for the expected spatial autocorrelation in yield within the crop field.

$$identity\ (mean\ Yield) \sim s(Distance) + s(X_{Coordinate}, Y_{Coordinate}) \quad [4]$$

$$logb\ (variance\ Yield) \sim s(Distance) + s(X_{Coordinate}, Y_{Coordinate}) \quad [5]$$

For each field model, we extracted the partial effect of distance on mean and variance -- *s(Distance)* terms (Figure 3). The overall edge effect was then summarized by fitting two GAMs for all individual partial effects on mean or variance yield (Equations 6 & 7).

$$partial\ effects\ on\ \text{"}mean\ Yield\text{"} \sim s(Distance) \quad [6]$$

$$partial\ effects\ on\ \text{"}variance\ Yield\text{"} \sim s(Distance) \quad [7]$$

2.5 Effects of landscape complexity on field-level mean and variance of canola yield

The 7-category land cover mapping in section 2.3 was reclassified into only two classes: crop (other crops and canola) and non-crop (water, barren/developed, wetland, grass/shrub, tree). Using this cover map, we described landscape complexity of each canola field by counting numbers of non-crop and crop pixels surrounding the field within various disks, ranging from 10 to 1000 meters (1 – 100 pixels) from the field boundary. To account for different field sizes, amounts of neighboring crop and non-crop pixels were normalized by each field's area. For each disk, we modeled field-level mean and variance as a function of the interaction between crop and non-crop edges using a GAM and a full tensor product (te) (Equations 8 & 9), which models both the main effects of these variables and their interaction.

$$identity\ (mean\ Yield) \sim te(Noncrop\ Edges, Crop\ Edges) \qquad [8]$$

$$identity\ (variance\ Yield) \sim te(Noncrop\ Edges, Crop\ Edges) \qquad [9]$$

3. Results

3.1 Effects of field edge on subfield-level mean and variance of canola yield

Both assessment methods showed evidence of higher canola yield at an intermediate distance into the field where yield-reducing “edge effects” are no longer dominant. The “edge effects” are visually apparent on plots of the mean yield (i.e., a low mean at the field edge, followed by a rapid increase from 0 to 30 meters; Figures 4a & 5a). While the bin-yield approach presents a subtle peak at 100 meters (Figure 4a), modelled mean yield peaked at 30 meters and gradually decreased toward the field center (Figure 5a). The field edge impacts on variance of yield were different between the two proposed methods. The “edge effects” are also clearly present in the yield variance, with much higher variance at the field boundary and a rapid decrease from 0 to 30 meters toward the field center (Figures 4b & 5b). However, while the bin-yield approach showed a gradual decrease of yield variance into the field (Figure 4b), the model predicted variance gradually increased from 30 meter toward the field center, indicating a potential stabilizing effect of the field edge on canola productivity apparent at around 30 meters into the crop.

3.2 Effects of landscape complexity on field-level mean and variance of canola yield

Partial effects of neighboring crop and non-crop land cover on mean yield are small (percent of deviance explained is only 2% to 3%) but consistently present a V-shaped pattern among all significant ring sizes (10 – 30 meters) (Figure 6). The effects are lower close to the two axes indicating that field-level mean yields tend to be lower if either crop or non-crop neighbors are dominant in the landscape. In those situations, higher landscape complexity—either more crop or more non-crop neighbors—would result in higher negative effect or lower mean yield. On the other hand, positive effects of landscape complexity on field-level mean were observed at the middle and right corner of the plot, indicating that canola fields have the potential to be more productive where there is a balance between non-crop and crop neighbors in the landscape. In that situation, higher landscape complexity would have higher positive effect on canola yield as indicated by higher positive effect toward the right corner of the plot.

Like the effects on mean yield, landscape complexity only represents a small (percent of deviance explained is only 2% to 4%) effect on field-level variance of yield across significant rings (10 – 80 meters) (Figure 7). Towards the bottom of the plot (i.e., field pixels have fewer non-crop neighbours), effects of landscape complexity on the variance of yield are low and negative, indicating that within-field variation of canola yield is less if the field is generally surrounded by crop land covers. Towards the left of the plot (i.e., field pixels have fewer crop neighbours), effects of landscape complexity follow a hump-shaped pattern, or intermediate optimum, with lower effects where there is either a low or high proportion of non-crop edges.

 # 4. Discussion

Effects of the field edges and landscape complexity on canola productivity:

Here we examined potential effects of the field edge and landscape complexity on mean and variance of canola yield at subfield and field-levels. Several studies have suggested a positive effect of landscape complexity on crop productivity. In a study about crop yields in the same temperate grassland region at a much coarser, county-level scale, *Galpern et al. (2020)* analyzed the relationship between yields of multiple crops and landscape complexity—measured as the amount of non-crop covers found nearby or within the field. We took that analysis further for canola by examining the potential effect of both neighboring crop and non-crop covers on the field-level mean canola yield. To account for effects of crop and non-crop cover simultaneously, we used a tensor product to model main effects and their interactions between the two types of edge. Our finding generally agreed with *Galpern et al. (2020)* that there is a plausible positive effect of field marginal habitats on mean canola yield, and canola fields surrounded mostly by non-crop covers may have lower yield, possibly due to the overwhelming yield-reducing "edge effect" in those fields. Fields surrounded mostly by crop covers also have lower yields, possibly due to a lack of ecosystem services supported by the presence of non-crop covers, such as pollination and pest control. Overall, we found a positive relationship between landscape complexity and field-level mean yield.

While a positive relationship between landscape complexity and crop productivity is measurable at the regional scale (can boost corn and wheat yields up to 20% as reported in *Nelson & Burchfield, 2021*), its economic importance to crop producers remains unclear. Thus, *Galpern et al. (2020)* suggested the potential benefits of landscape complexity be explored at a finer scale to determine how different types of field edges contribute to yield and to estimate the limits of any effect. That valuable information would help producers to manage or redesign their fields. To support this objective, we assessed the potential impacts of field edge to subfield-level yield. We found evidence of a boost in yield between 30 and 100 meters from the field edge towards its center. There is also a plausible yield stabilizing effect at the same range. Although both potential boosting and stabilizing effects are quite small, these two effects together may offer enough benefit for producers to add small amounts of different land covers within or nearby their fields or, equally provide incentive to retain the current configuration of non-crop covers within or near their fields.

Limitations and future directions:

Our study relies heavily on an accurate land cover map to identify precisely both field boundaries and their neighboring land covers. Here we generated a land cover map of the study area from Sentinel-2 imagery using the ACI layer as training and testing dataset. The overall accuracy of our land cover map is quite high (about 90%), especially for canola with both producer's and user's accuracy of above 95%). However, there remain potential issues with that cover map. Although locations and overall shapes of canola fields were often detected correctly, precise field boundaries and neighboring covers are much less accurate because misclassifications are more likely to occur at edges between different cover classes due to the mixed pixel problem. In addition, we mapped land cover at 10-meter resolution which is larger than many edge features, such as small roads, shelterbelts, and some wetlands, etc. Thus, those features may not be presented correctly in the map. To reduce classification errors, we manually inspected every individual field to make sure that its boundary and neighboring land covers were properly mapped. This manual inspection, however, cannot be done easily over a large area. Higher resolution imagery (< 5-meter resolution) should be investigated to provide more accurate land cover maps for future studies.

A solution to reduce the likelihood of misclassification at the field edge that we adopted is to merge land cover types to broader categories. Here we only considered two types of edges: crop versus non-crop covers. Although this solution helps to improve accuracy of land cover map (e.g., *Galpern et al 2020*), it also prevented us from analyzing the effects of different edge types. It is possible that we would expect different effects associated with roads, shelterbelts, hedgerows, wetlands, and other non-crop covers found in agricultural landscape, as the different vegetation, soil and moisture characteristics of these features may influence the amount and type of ecosystem service provided. Future studies using land cover maps with higher thematic resolution are necessary to explore the effects of different edge types.

Our analysis also relies on precision canola yield maps derived from Sentinel-2 imagery and another precision yield dataset. Although, our yield model performed reasonably well with prediction accuracy within 12-16% accuracy of reference yield and be able to capture within-field variation. It is still worth noting that our model was built using training data from only 8 canola fields—a very small number given the much large study area (100 × 100 km). This training dataset might not fully capture canola growth dynamics and its corresponding spectral response. Future studies should try to use a large training dataset to build a more accurate yield model which, from a data acquisition perspective, is feasible given that precision agriculture has been long used in Canada and up to 85% of producers have yield monitor with their machines. In the yield model, we also did not use any ancillary data which are common inputs of crop yield mapping, such as soil moisture, climatic conditions, crop variety, or agricultural practices, in any of our models. Those variables are available as remote sensing products and could be considered in future studies to improve the predictive accuracy of yield models.

This study focused on a single crop (canola) for only one year (2019) over a relatively small study area (given that this crop is grown across a continuous footprint ~500,000 km^2 in area; estimated from *AAFC, 2019*). Thus, although our findings are promising, they may not hold true in other crops, years, or sub-regions of the Canadian Prairies. To confirm the validity of our findings, more studies conducted in regions with contrasting environmental conditions are needed. In addition, to make those findings more meaningful for crop producers, future research needs to translate a plausible positive effect of the field edge to economic value, such as profitability.

5. Conclusion

This study is the first to utilize remote sensing imagery and a precision agricultural dataset to assess impacts of field edges on crop productivity. Research on this topic using the conventional, controlled experiment has been rather limited and has occurred chiefly in a few small-scale studies, likely due to the high cost of field campaigns. The remote sensing approach we demonstrate provides many more opportunities to assess the potential impacts of field edges on crops. The method can be implemented at low cost across a large area, capturing a variety of landscape conditions and for multiple crop-years using readily available satellite images and precision agricultural datasets.

Our results suggested that neighboring non-crop spaces not only create a boost in canola yield but also help to stabilize crop productivity. Although the boosting and stabilizing effects of the field edge may be subtle, retaining non-crop spaces near the field could still be a beneficial option for producers, especially given the cost of removing non-crop spaces and current efforts and incentives for the conservation of natural habitats in the region. While the idea of adding non-crop features, such as wildflower strips, or hedgerows, to help increase crop productivity is receiving more attention, our findings about the effects of the field edge on subfield-level canola productivity suggest that producers already benefit from these features and contribute to discussions about the optimal design of fields and for increasing landscape complexity.

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Figure Captions

FIGURE 1. Study area: selected canola fields (in yellow) on top of the 2019 Sentinel-2 RGB image (median values). A sample field (in red box) and its "distance-to-nearest-edge" raster are shown in panel A and B.

FIGURE 2. Outputs of functional regression model to map precision canola yield for all studied fields (a and b) and observed versus predicted yield for a sample field (c and d).

FIGURE 3. Partial effects of distance on mean (a) and variance (b) yield for a sample canola field. Numbers within the y-axis labels are effective degrees of freedom - a proxy for the degree of non-linearity in predictor-response relationship where 0 implies no relationship, 1 implies linearity, and >1 implies non-linearity.

FIGURE 4. Mean (a) and variance (b) bin-yield of various distance bins for all canola fields (black dots). The overall impacts of field edge on subfield-level canola productivity are presented by mean $\pm$ 1σ lines across all distance bins.

FIGURE 5. Partial effects of distance (black lines) on mean (a) and variance (b) subfield-level yield and the overall impacts of field edge (blue lines) captured by GAMs.

FIGURE 6. Partial effects of neighboring crop and non-crop spaces on field-level mean yield. The effects are no longer significant for 40-meters and larger rings. Values shown in the tittles are ring size, p-value, and percent of deviance explained. Each black dot presents an individual canola field. Black arrows show directions of increasing landscape complexity.

FIGURE 7. Partial effects of neighboring crop and non-crop spaces on field-level variance yield. The effects are no longer significant for 90-meters and larger rings. Values shown in the titles are ring size, p-value, and percent of deviance explained. Each black dot presents an individual canola field. Black arrows show directions of increasing landscape complexity.

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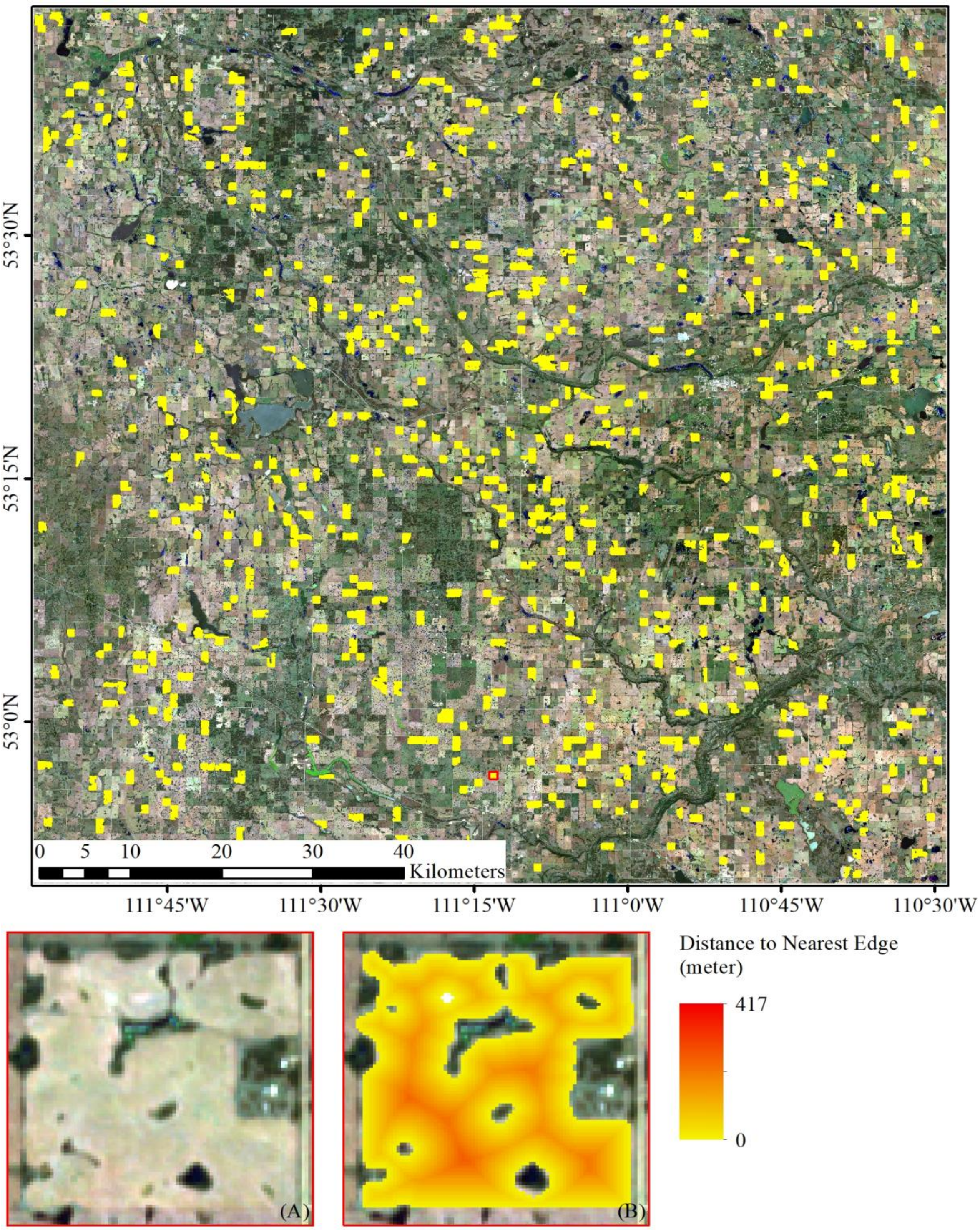
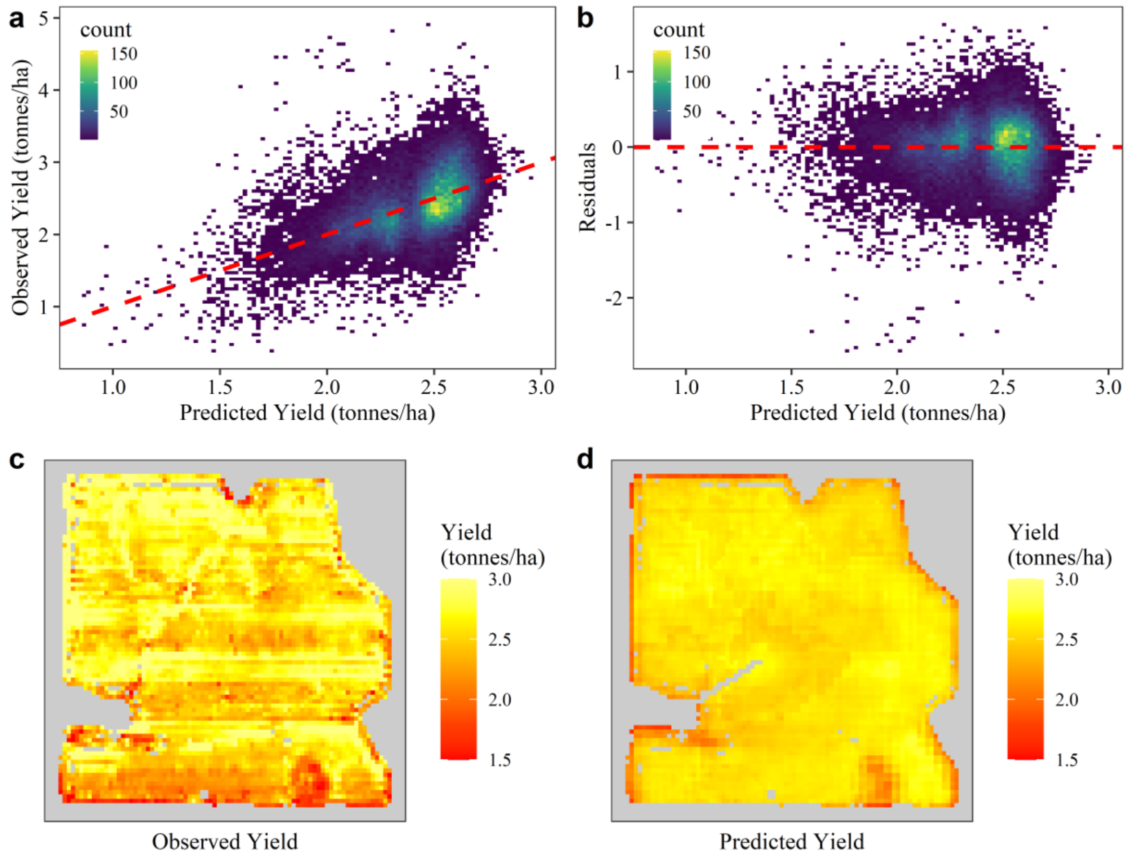


FIGURE 1. Study area: selected canola fields (in yellow) on top of the 2019 Sentinel-2 RGB image (median values). A sample field (in red box) and its "distance-to-nearest-edge" raster are shown in panel A and B.



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417 FIGURE 2. Outputs of functional regression model to map precision canola yield for all studied

418 fields (a and b) and observed versus predicted yield for a sample field (c and d).

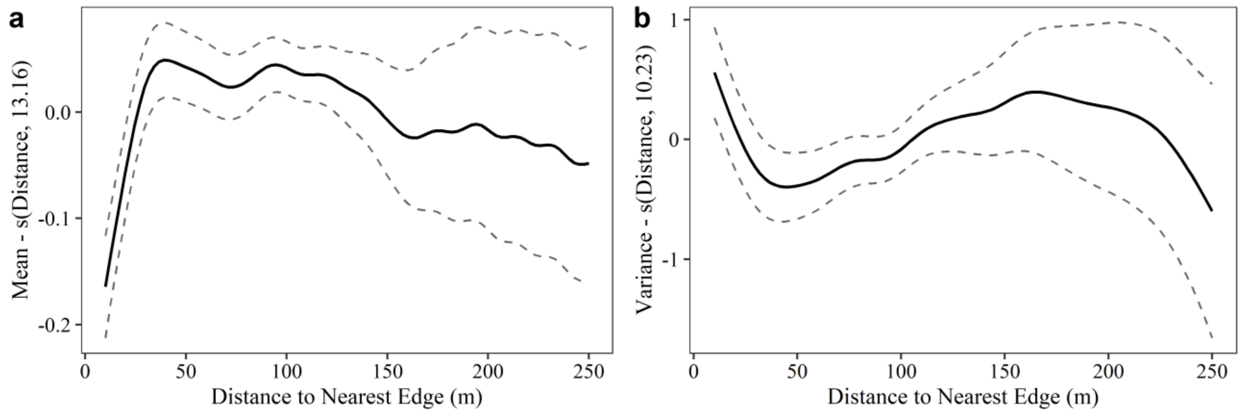

FIGURE 3. Partial effects of distance on mean (a) and variance (b) yield for a sample canola field. Numbers within the y-axis labels are effective degrees of freedom - a proxy for the degree of non-linearity in predictor-response relationship where 0 implies no relationship, 1 implies linearity, and >1 implies non-linearity.

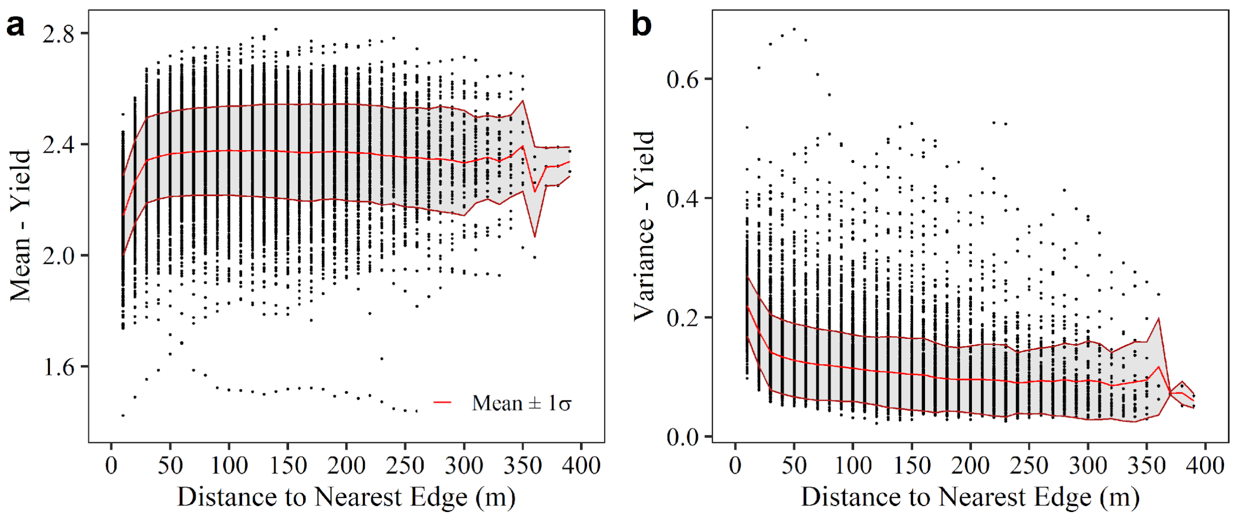

FIGURE 4. Mean (a) and variance (b) bin-yield of various distance bins for all canola fields (black dots). The overall impacts of field edge on subfield-level canola productivity are presented by mean ± 1σ lines across all distance bins.

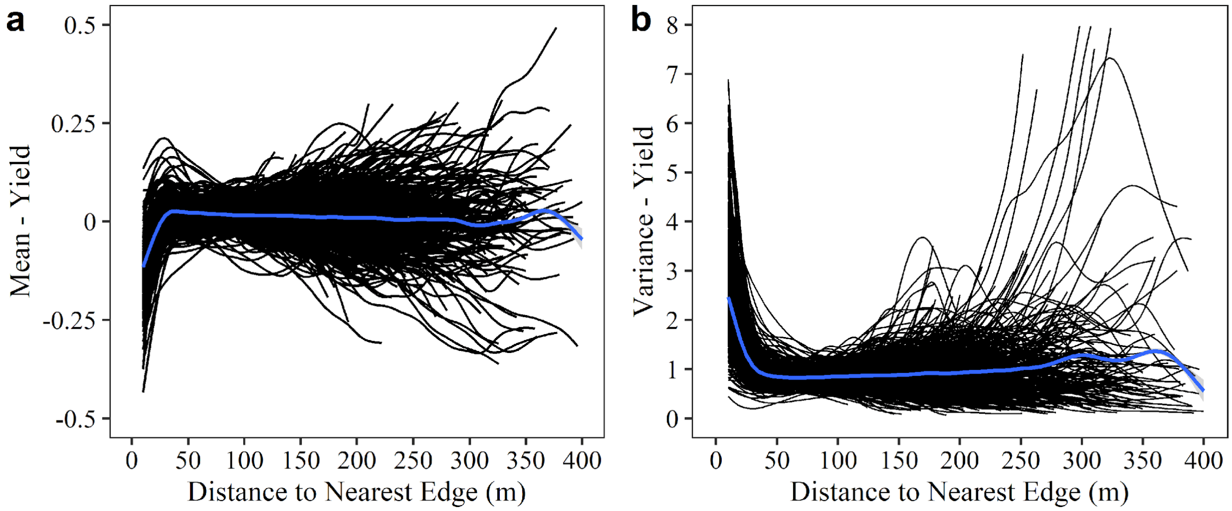

FIGURE 5. Partial effects of distance (black lines) on mean (a) and variance (b) subfield-level yield and the overall impacts of field edge (blue lines) captured by GAMs.

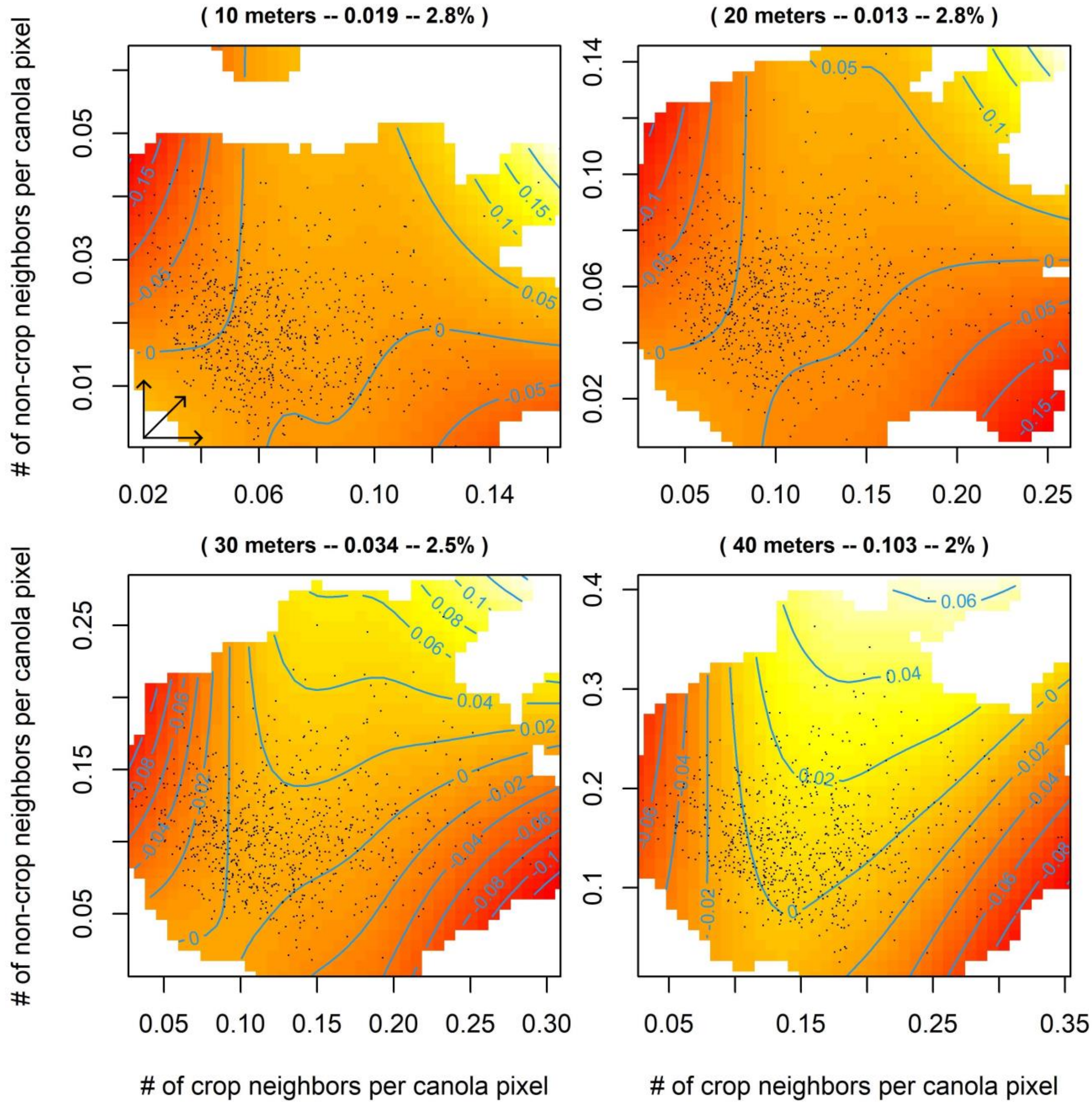

FIGURE 6. Partial effects of neighboring crop and non-crop spaces on field-level mean yield. The effects are no longer significant for 40-meters and larger rings. Values shown in the tittles are ring size, p-value, and percent of deviance explained. Each black dot presents an individual canola field. Black arrows show directions of increasing landscape complexity.

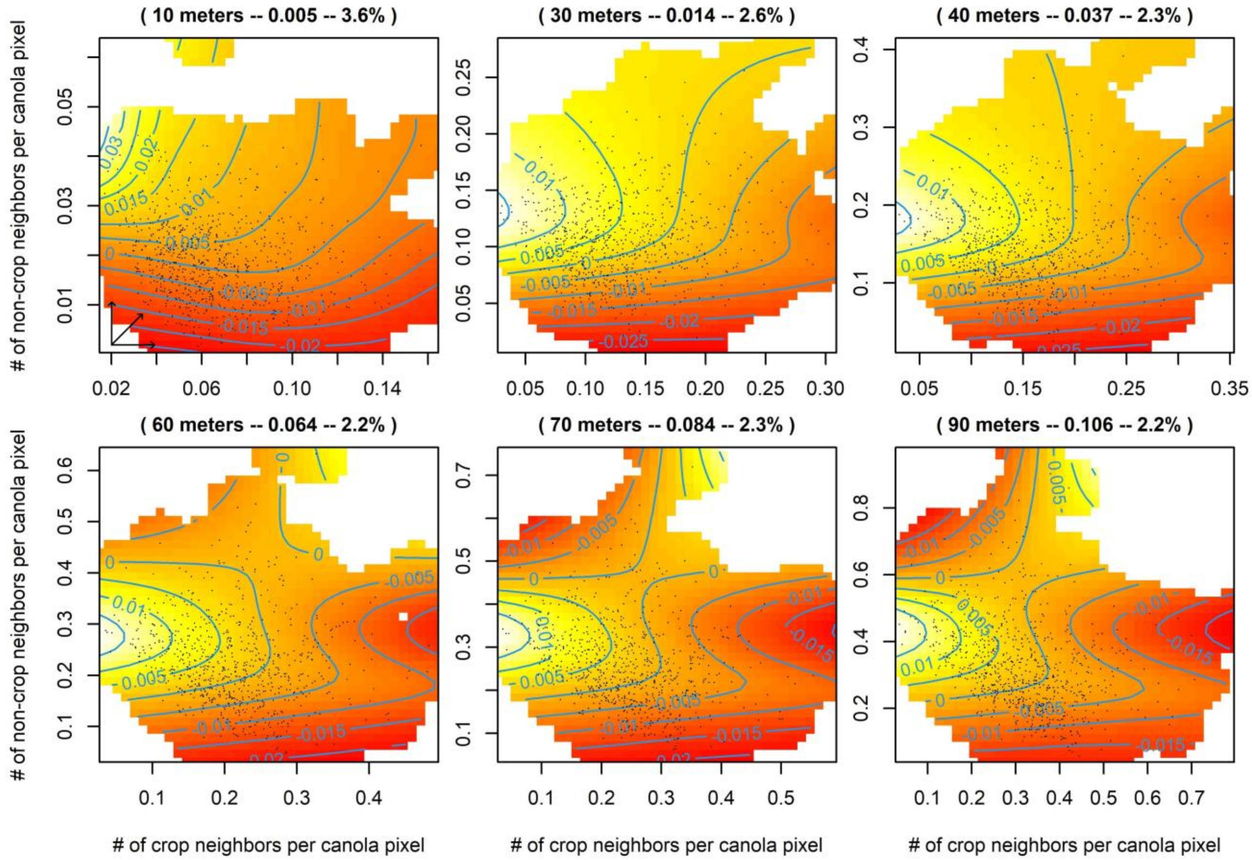

FIGURE 7. Partial effects of neighboring crop and non-crop spaces on field-level variance yield. The effects are no longer significant for 90-meters and larger rings. Values shown in the titles are ring size, p-value, and percent of deviance explained. Each black dot presents an individual canola field. Black arrows show directions of increasing landscape complexity.