Incorporating Return on Investment for Profit-Driven Management Zones

E. Lord[1]*. E. Fallon[1], A.A. Boatswain Jacques[1,2], A.B. Diallo[2], A. Cambouris[3]

[1]St-Jean-sur-Richelieu Research and Development Centre, AAFC, 430 Gouin Boulevard, Saint-Jean-sur-Richelieu, J3B 3E6, Canada.

[2]Université du Québec à Montréal, Département d'informatique, 201, av. Président-Kennedy, local PK-4150, Montréal, QC, H2X 3Y7, Canada

[3]Quebec Research and Development Centre, Agriculture and Agri-Food Canada (AAFC), 2560 Hochelaga Blvd., Quebec City, QC G1V 2J3, Canada

* Corresponding author: etienne.lord@agr.gc.ca

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Abstract.

Adopting site-specific management practices such as profitability zones can help to stabilize long-term profit while also favouring the environment. Profitability maps are used to standardize data by converting variables into economic values ($/ha) for different cropping systems within a field. Thus, profitability maps can be used to define management zones from several years of data and show the regions within a field which are more profitable to invest in for production, or those that can be converted to other agricultural activities.

In this study, we evaluated different algorithms devised to best divide a field into distinct zones in order to optimize profitability, with the premise of converting one part of the field into another crop, or into other ecoservices. We used the maximization of the return of investment (ROI) values, instead of the profitability, in our simulations. Two division strategies were investigated, either a 50/50% split of a 70/30% split, keeping the biggest field portion as the main cropping area. In order to evaluate the strategy, ROI and profitability maps were developed by aggregating yield data (2016 to 2021), from 10 fields originating from 6 distinct producers in Quebec, Canada. Then, two different algorithms were evaluated, one algorithm creating field bipartitions, and another one using a knapsack with backtracking strategy in order to select the most profitable zones to be conserved. To assess the best solutions, field divisions were created using the 2016 ROI map, while resulting profits were estimated using the remaining years (5 years).

We report that using our bipartition strategy, a 1-2% gain was obtained, in contrast to some randomly equivalent bipartitions (P<0.01). In contrast, using, the knapsack with backtracking algorithms, we observed profit gains averaging ~ 7.8% (50/50%) and ~6.7% (70/30%) after the five-year period. However, the use of this algorithm resulted in unrealistic divisions of the fields and highlighted the possibility of creating better subfield division algorithms.

In conclusion, we verified some advantages of using ROI maps to divide a field into two subfields, conserving the region generating the most positive ROI. In the future, we want to improve our algorithms to take into account more complex field divisions, for example presenting multiple crops and taking into account multi-year information layers such as weather and soil properties.

Keywords.
Site-specific management zones, optimization, knapsack algorithms, profit mapping, digital agronomy.

Introduction

Reconciling economic prosperity and ecological services at the farm level is among the greatest challenges that agriculture industry will be facing in the coming decades (Rockström et al., 2017). Producers using yield monitors nowadays have access to multi-year yield maps, allowing them to identify where yields are stable or variable (Basso et al. 2016). Using those zones and economic information such as crop market price, input prices, incomes and variable costs, producers and agronomists can create profitability maps. Kitchen et al. (2005) studied how profitability maps could be used for on-farm conservation practices and found that this approach enabled them to meet conservation needs such as surface water quality, soil health (erosion) and ground water quality simultaneously with profitability improvements. They also concluded that it is important to identify local factors influencing profitability when considering net loss mitigation practices in order to address the situation properly.

There will often be locations on a field where yield will be consistently low or limited (Muth, 2014). By focusing on an approach where return on investment (ROI) is prioritized, the land manager can adjust his planning to guarantee a better revenue for the dollars invested on this portion of his fields. Coupling high resolution precision data with simulation tools or software can help identify where nutrient loss factors are elevated (Basso & Antle, 2020). However, to simultaneously increase profitability of a field, a deeper understanding of the traditional field performance metrics is required.

For this study, our hypothesis was that it was possible to divide a field into two distinct zones, in order to optimize profitability for one of the zones, thus reducing potential lost for a producer. Our target was either a 50/50% or a 70/30% split. Different approaches have been explored for the generation of management zones using either empirical thresholding, *k*-means clustering, fuzzy clustering, integer linear programming and machine learning (Velasco *et al.* 2023). We revisited the branch-and-bound approach (Cid-Garcia *et al.* 2013) by using a binary knapsack algorithm as well as a new bipartition algorithm in order to select some management zones based on ROI. We used only one ROI map (2016) and validated the field divisions using the total profitability over the 5 next years (2017-2021) since our goal was only to investigate the potential of using ROI for the zone creation.

Methodology

Fields studied and ROI calculations

Raw yield, agronomic, economic and production data from 10 fields in Quebec (Canada), were bought from participating producers using either a corn-corn, corn-soybean or a corn-soybean-wheat rotation in their fields. The dataset included 6 years of production, spanning from 2016 to 2021. Before map creation, all agronomic and economic information was manually verified to remove any erroneous values, and total field yield and agronomic practices for each crop type were compared to other fields in the same area, to ensure representative cropping management and yield. Yield data points were then cleaned and converted into 10m^2 zones, using custom python scripts in Arcgis Pro software (Esri, version 3.3.0), taking into account the combine direction and speed.

All economic data were converted into equivalent \$/ha, before being scaled to a 10m^2 grid resolution using the software R version 4.3.1. Total profit in each field was calculated using the procedure of Massey *et al.* (2008), by including in cost the following categories: operating expenses, seeds, fertilizers, pesticides, transport cost, harvest association fees, interest, equipment maintenance, fuel/natural gas, combine cost, dryer cost and other depreciation. Finally, ROI was calculated by dividing individual zone value by the zone associated cost. Figures were generated to manually inspect the resulting maps, using the R package ggplot2 (version 3.4.4), before simulations were carried out.

Algorithms and Simulations

A first bipartition algorithm was developed using graph partitioning (Lord *et al.* unpublished), where the initial nodes, representing each $10m^2$ ROI zones, are linked to their adjacent neighbours. The algorithm then executes different cuts and random walks in the resulting graph under the constraints $\sum R_{xy} < \text{maximum allowed } surface$ and $\text{minimum } ROI > 0$ and while maximizing the subregion potential ROI, where R_{xy} represent the inclusion [0,1] of the ROI of each zone located at the specified longitude (*x*) and latitude (*y*) geolocation.

The second algorithm used was a binary knapsack (Horowitz et Sahni, 1974) using different subfield partitions of the original field as inputs, with the same constraints. For our application, rectangular regions with a minimum size of 20 x 40 m or 40 x 20 m were used. The optimal field surface was computed by removing any region with negative or zero ROI.

Simulations were carried out by using as input the 2016 ROI map, then calculating the resulting profitability over the 5 subsequent years (2017-2021), without recalculating the variable cost (*e.g.* fertilizer, fuel). Statistical significance was evaluated using bootstrap resampling using random generated bipartitions of the field having the same target surface ±1% to account for uncertainty.

Results and Discussion

Our simulations took into account 10 fields with an overall field size of 12.9 ha ± 9.2 ha. In order to realistically account for environmental and economic factors, we simulated the division of the field in 2016, and evaluated the division solutions by calculating the successive profits, or loss, resulting from the years 2017 to 2021 (5 years). In total, 63 single ROI and profit maps were generated and analyzed.

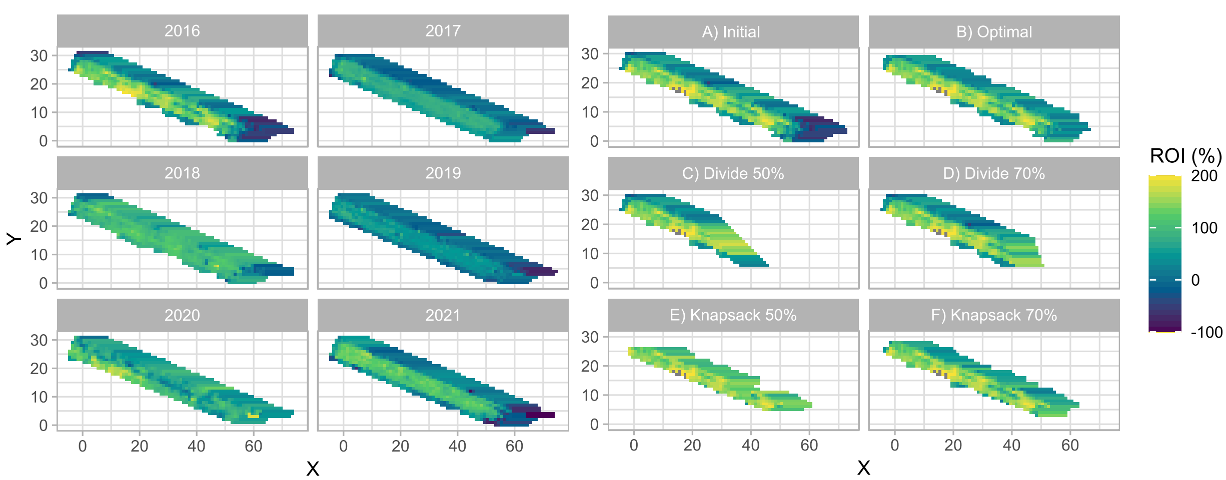

Fig 1. Examples of optimization where the knapsack algorithm removed all field boundaries (right – E and F). ROI map for a 5.4 ha field divided in $10m^2$ zones. Initial ROI map 2016-2021 (left) and 2016 ROI map after division into subfields (right). In A) Initial field in 2016; B) Optimal map without negative ROI zone; C) Conserved region after 50/50% split division with bipartition; D) Conserved region after 70/30% division with bipartition; E) Conserved region after 50/50% split with knapsack algorithm; F) Conserved region after 70/30% split with knapsack algorithm. Percent total profit for the remaining 5 years compared to the original for B) 93.5%; C) 53.8%; D) 73.3%; E) 65.9% F) 84.1%.

Overall, the bipartition algorithm resulted into an average of 20,860 scenarios evaluated for each field. In contrast the binary knapsack algorithm resulted into an average of 20,907,055 scenarios for each field. Algorithmic optimization could reduce the number of scenarios being evaluated for the knapsack algorithm (Ali *et al.* 2021). However this was not needed for this study.

Figure 1 presents an example of the original field ROI map (Fig.1A),and the resulting partitions into subfields. For this example, we can observe that the right bottom portion of the field was removed using our partition strategy, resulting in a 53.8% (50/50% division) or 73.3% (70/30% division) total profit for the remaining 5 years compared to the initial.

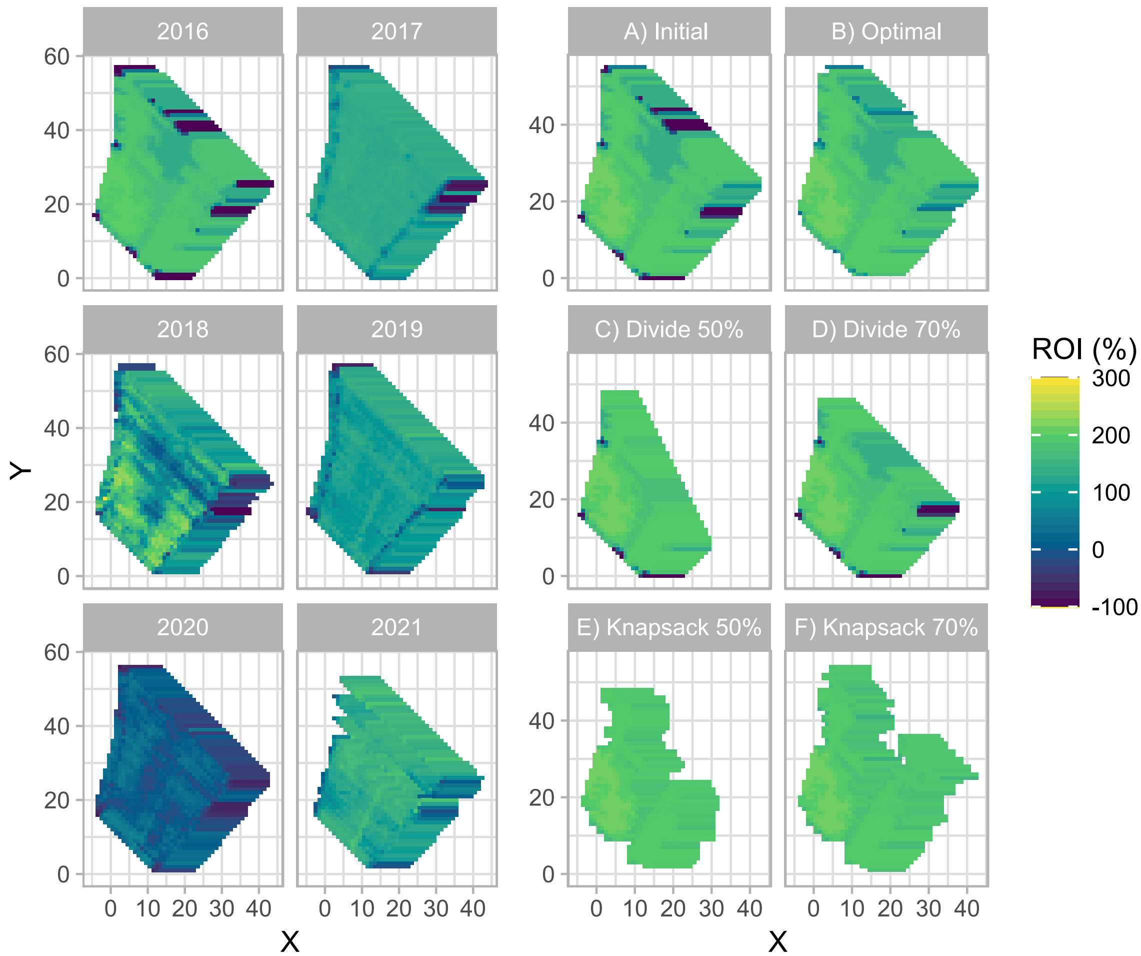

Fig 2. Examples of the subfield division algorithms with an irregular-shaped field. ROI map for a 11.1 ha field divided in 10m^2 zones. Initial ROI map 2016-2021 (left) and 2016 ROI map after division into subfields (right). In A) Initial field in 2016; B) Optimal map without negative ROI zone; C) Conserved region after 50/50% split division with bipartition; D) Conserved region after 70/30% division with bipartition; E) Conserved region after 50/50% split with knapsack algorithm; F) Conserved region after 70/30% split with knapsack algorithm. Percent total profit for the remaining 5 years compared to the initial in A, for B) 98.9%; C) 53.5%; D) 71.9%; E) 55.1% F) 74.9%.

In contrast, the knapsack algorithm resulted in the removal of the field outer borders, which represent low ROI regions, and indeed represent a higher profitability scenario (Fig.1C vs Fig.1E 53.8% vs 65.9%, 50/50% division), representing a 12.1% difference for the same management zone superficies.

For a field presenting some higher ROI zones and an irregular shape (Fig. 2), the same scenario was observed using both algorithms, with a smaller gain in profitability over the baseline of 50% or 70% total area (53.8% vs 50.0%, p<0.01, Fig.2C) and (73.3% vs 70.0%, p<0.01, Fig. 2D) using the bipartition algorithm. Higher profitably ratios were found for the knapsack algorithm (Fig. 2E and 2F).

Finally, Figure 3 presents an example of one solution where low ROI zones where conserved by the bipartition algorithm (Fig. 3C and 3D, bottom right corner of the field). While not optimal after evaluation of other scenarios, both scenarios (50/50%) and (70/30%) resulted in small profit gains over the baseline. Again, higher profits were found using the knapsack algorithm.

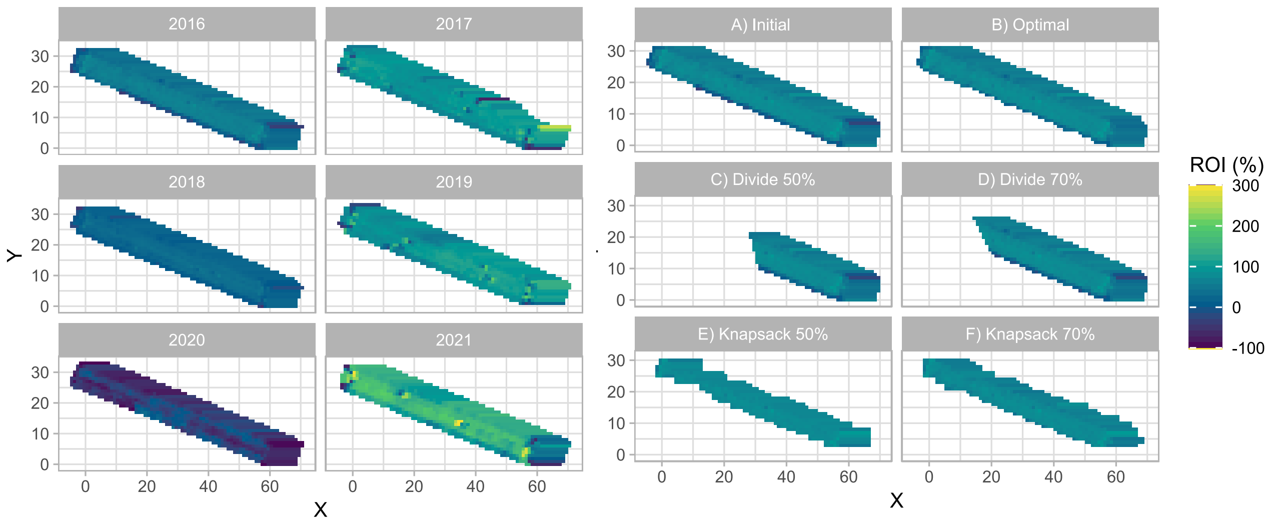

Fig 3. Example where the bipartition algorithm keep the low ROI zones (right – C and D). ROI map for a 5.7 ha field divided in 10m^2 zones. Initial ROI map 2016-2021 (left) and 2016 ROI map after division into subfields (right). In A) Initial field in 2016; B) Optimal map without negative ROI zone; C) Conserved region after 50/50% split division with bipartition; D) Conserved region after 70/30% division with bipartition; E) Conserved region after 50/50% split with knapsack algorithm; F) Conserved region after 70/30% split with knapsack algorithm. Percent total profit for the remaining 5 years compared to the original for B) 97.2%; C) 50.8%; D) 71.4%; E) 60.3% F) 80.1%.

For the 10 studied fields, the 70/30% division using the bipartition algorithm resulted in 71.1±0.1% of the original profit, thus preserving and increasing overall profitability by ~1% over the 5-year periods. In contrast, using the 50/50% division, our algorithm resulted in 52.0%±3.7% of the total profit. Overall, this indicates that using our algorithm result in some gain over what would be expected by a random 70/30% or 50/50% division of the field ($p<0.01$). However, the higher standard deviation for the 50/50 split indicates that suboptimal solutions were also generated for those divisions.

Overall, while both our approaches improved the overall expected profitability over random partitioning of the field, only the bipartition algorithm provided realistic division of the field, providing a ~1-2% return. These preliminary results encourage us to pursue further exploration of these algorithms. It also confirms the possibility of using ROI maps in delimiting management zones, which was proposed by some authors (Muth, 2014).

Limitations

There are some drawbacks to our simulations. First, we only considered the removal of one of the regions of the map in our calculation. Thus, we did not consider a replacement crop in the removed region, under the hypothesis that the conversion could be at null cost to the producer, but would not generate additional profit. Another drawback was that our simulation used precalculated static maps. In reality, many of the costs related to the analyzed fields are directly related to the cultivated area such as fertilizer, seed, pesticides, and fuel cost. Those would need to be recalculated for each map, year and scenario to better represent the real profit generated by the conserved field, without the removed region.

Furthermore, we purposely created our initial simulation based on 2016 ROI map, in order to have 5 years of remaining field data to validate our division scenarios. However, creating the division of the field another year (*e.g.* 2017) could yield a final total profit higher for a specific field or subfield for the subsequent years. This happened in 2 out of the 10 evaluated fields, leading to a total profit that could be increased by 4.1% to 4.9% over those 5 years, if the division scenarios were carried out in 2017. Thus, possible algorithm optimization could be applied, possibly using the addition of ancillary data such as soil properties and weather, to determine the optimal division (Maestrini et Basso, 2021). Gili *et al.* (2017), which used different *k*-means algorithms to improve resource allocation by generating clustered version of profit map, also concluded that soil structure and properties should be included when researching crop management goals. Furthermore, since weather could also mask some potential productivity patterns among zones for a particular growing season, the annual weather data could also be included in the simulations (Basso et al. 2016).

Summary

We presented here two algorithms and different simulations for the division of a field into two distinct regions. This approach was motivated by the need to evaluate different scenarios related to field conversion and to evaluate if field division, based on ROI, could achieve a gain over a simple division based on yield maps, such as the farming-by-yield approach (Basso et al. 2016). Our results, using two algorithms, seems to demonstrate some potential gains in using this approach to remove some unprofitable regions from production. Furthermore, our novel bipartition algorithm was able to create realistic divisions, that could be used by producers.

In the future, we want to further improve this methodology by adding more parameters to the simulations including alternative crop use and multi-year simulations. Furthermore, while we focused on removing strictly negative ROI regions in this study, we could increase this constraint to ROI regions presenting less than 100% ROI. Furthermore, recalculating the total cost of each field region dynamically, after each bipartition scenario, could result in more precise estimation of the potential profitability.

With the improvement of yield and soil monitoring with precise geolocations, the development of new machine learning algorithms capable of analyzing those complex datasets could improve our agricultural land use and management practices. While still uncommonly used by producers, computer simulations and digital agriculture might help them shift unprofitable fields into profitable land when considering alternatives cropping practices.

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