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Evaluation of Grain Quality-Based Simulated Selective Harvest Performed by an Autonomous Agricultural Robot

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Abstract: Grain price differences due to protein content can have economic effects on the farm as well as environmental effects when alternative protein sources are imported. Grain protein variability can vary from year to year due to environmental factors and can be addressed by site-specific management practices. Alternatively, it can be addressed at harvest time by selective harvest. Agricultural autonomous robots can accurately follow alternative harvesting routes that are subject to grain quality maps, making them suitable choices for selective harvest. This study addresses therefore the potential revenue of selective harvest performed by the route planner of an autonomous field robot. The harvest capacity and potential economic revenues of selective harvest in a Danish context were studied for a set of 20 winter wheat fields with four hypothetical scenarios. The results showed significant differences in harvest capacity between conventional and selective harvest. Even though in some scenarios selective harvest did not require notable additional harvest times, the cost–benefit analysis showed small economic returns of up to 46 DKK ha^{-1} for the best scenarios, and for most cases losses up to 464 DKK ha^{-1}. Additionally, the location of the high protein content areas has great influence on the profitability of selective harvest.

Keywords: smart farming; selective harvest; agricultural field robots; autonomous agricultural robot; harvest automation; grain quality orientated harvest; Internet of Things; optimised route planning

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1. Introduction

Grain prices depend on their protein content and have economic consequences, as farmers are forced to increase the import of protein sources to fodder or obtain lower prices for their grain crops due to different end-use functionalities, e.g., flour milling contrasted with starch manufacturing [1–3]. The import of alternative protein sources, e.g., soybeans (*Glycine max* L.), is not only expensive for the farmer, but it also has important environmental consequences, such as biodiversity losses [4] or increased emissions of greenhouse gasses [5]. Even though nitrogen fertilisation and cultivars have a direct effect on the protein content of the grain [1,3,6], the harvest year and other environmental factors can have an even higher influence [2,7–9]. These factors do not only affect the overall crop quality in a field, but can also create important variations within the field [10,11]. Besides protein content, other variables can also define the quality of the grain, which has an influence on its final use as well as price, e.g., mycotoxin infections [12] or grain moisture [3,13].

Since the Global Positioning System (GPS) technology was made globally available without deliberate quality degrading, conventional agriculture started to move into precision agriculture where in-field variability can be addressed by variable rate applications as well as other site-specific management practices [11,14,15]. These site-specific management techniques aim to improve the grain quality and quantity, and make the use of resources more efficient, which improves the economic return of the farm [6].

Alternatively, infield grain variability has also been proposed to be addressed at harvesting time through selective harvest (SH), where grain is harvested separately according to its predetermined quality, e.g., protein content. Separating grain by quality during harvest can be employed to capture grain price premiums, as some markets categorise some grains into grain quality groups [16–19]. The cost–benefits of SH have specifically been studied by the grain price differences of wheat based on protein content [18–20] as well as mycotoxin infections [12], concluding that there is potentially measurable total profits to be gained for SH. Ref. [12] found potential gross profits of 48 GBP ha^{-1} for SH in regard to wheat mycotoxin infection. Ref. [18] found that segregating wheat grain between 12% to 14% in protein content can provide a marginal return between 2.94 USD Mg^{-1} to 5.51 USD Mg^{-1}, respectively. Ref. [19] found potential profits of more than 32 EUR ha^{-1} in some cases of SH of wheat, while [20] found that dividing the fields in management zones that were harvested selectively gave losses in some scenarios while in others extra revenues of, e.g., 9.53 AUD ha^{-1}.

Different SH strategies have been presented in the scientific literature. One of the strategies consists of separating the grain stream into two bins in the combine during the harvest. This can be achieved by either real-time measurements [17,21], or by predicting the grain quality based on the locally variable environmental conditions [13,22], or by a combination of modelling and monitoring [23]. A simpler approach can be accomplished by actively monitoring the grain flow to redirect and optimise the processing and marketing of the harvested batches independently [16,24]. Finally, a different strategy is to divide the field into management zones, which are then harvested selectively [12,19,20]. Each of these SH strategies present different challenges, e.g., reduced grain tank capacity when two bins are implemented in the combine harvester, too high variations in the values generated by sensors that increases the difficulty of segregating the grain stream by a diverter valve in a combine with two bins, or the reduced scalability of the grain quality predictive models. Regarding SH by management zones, the different approaches found in literature do not cover the practical aspects of harvesting selectively, as they estimate the extra harvesting costs by the harvesting distances to be covered but do not consider the additional distances of the connection paths and turning areas, or the practical issues of how the harvester operator can distinguish the different management zones from each other in order to harvest selectively.

Thanks to the Internet of Things (IoT) applied to agriculture, robotics and autonomous vehicles can perform in the near future the same field operations that currently rely on traditional human-agricultural vehicle interactions [25–30]. Furthermore, autonomous agricultural robots can operate in fields accurately following site-specific and optimised route plans that are presently challenging for human operators with the newest machinery, even if assisted by smart navigation devices (e.g., [31]). Optimised route planning has been successfully implemented in harvesting operations with the advantage of improving the harvest capacity of the vehicles and saving operational time [32–36], which as a result reduces the risk of soil compaction [25]. In addition, optimised route planning can also be used to redirect the routes according to infield spatial variations [37,38]. Therefore, autonomous agricultural robots and optimised route planning have great potential to be employed in SH. Agricultural vehicle robots have the advantage of following accurately a specific SH route that is different from the conventional harvest route and that can not necessarily be visible in the field to the human eye. In addition, the recent technological advances in monitoring, remote sensing and modelling are allowing rapid non-invasive methods to reliably map the grain quality of a field prior to harvesting [10,39]. In order to avoid the challenges of segregating the grain into two bins while harvesting a new approach is studied in this manuscript, where the route plan of a robotic harvester is determined by a grain quality map so that the different qualities are harvested separately at different times. Similar to the management zones presented by [12] and by [20], the SH strategy studied in this paper relies on reliable grain quality maps that may be generated by machine learning as well as scientific models or by remote sensed measurements (e.g., [2,40–42]). However, ref. [12] does not describe how harvesting the different management zones would take place, as the study focuses mainly on the management zone creation and the cost–benefit analysis of SH and variable-rate applications. Additionally, [20] also does not address the practical issues of route planning in the SH proposed in their study, even though they do take into consideration diverse driving directions and the subsequent extra distances to drive during harvest in their calculations.

SH can address some of the sustainability issues associated with the suboptimal conventional harvest, which consider the whole field uniformly. Grain quality indicators such as mycotoxin concentration, moisture content or protein content directly affect its processing and possible end-usage, which can imply grain downgrading [43], food contamination [44] and ultimately food waste even if some parts of the grain are recognised high-quality [45] with subsequent social, environmental and economic consequences.

This study addresses the potential revenue of harvesting separately higher grain quality areas from the remaining part of the field by the use of an autonomous field robot. Autonomous agricultural robots have the advantage of reliably following a route plan that addresses the quality areas in a field that are not necessarily visible by the human eye. Additionally, this study takes into consideration the full implications of the route alterations of SH in specific designed cases. It is hypothesised that selective harvesting based on assessed infield protein content variability is economically feasible in a Danish farming context. Consequently, the aim of this study was to (a) determine the harvest capacity of SH in different scenarios against conventional harvest; and (b) examine the potential economic benefits of harvesting selectively winter wheat in a Danish context. To achieve this, a set of fields with hypothetical grain quality scenarios were studied by the use of route planning simulations for an autonomous agricultural robot.

2. Materials and Methods

2.1. Route Planning with Autonomous Field Robot

The simulated task times are based on the route planner of the autonomous agricultural robot Robotti (Agro Intelligence ApS, Denmark, Aarhus), which was first described in [46], and later mentioned in [47]. An up-to-date description of Robotti can be found in its homepage [48]. Robotti is designed to carry and operate a varied range of implements, but can currently not perform grain harvest operations. Nonetheless, the route planner that directs the robot across the field can make plans that can be employed for harvest operations, where the headlands are harvested first and the main field area thereafter. In order to perform selective harvest, it is assumed that the areas with high quality grain are smaller than the rest of the field with lower quality. The field is then harvested considering the high-quality (HQ) areas as subfields or obstacles to avoid when harvesting the lower quality crop. Once this part of the field is fully harvested, the high-quality areas are then harvested and the grain is loaded on trailers to be stored independently from the rest of the harvested grain. For the simulations, the autonomous harvester robot is assisted by two grain carts with 10 Mg of capacity each.

To assess this future scenario some assumptions are required to make the analysis comparable: (a) the storage capacities are equally distanced from the harvested fields and are close enough, so that two grain carts are sufficient to assist the robot harvester without waiting times; and (b) there is a uniform yield distribution across the fields.

The route planner method used in this study intentionally follows a row-by-row approach which emulates conventional harvest and reduces the potential influence of the heuristic optimisation method employed. The Tabu search algorithm of the route planner optimises the connections between rows and work areas. The estimated total operational times by the route planner are based on a set of inputs. They also include the vehicle kinematics in the calculations, i.e., accelerations and decelerations, as well as the steering dynamics. The route planner also takes into account the driving time from the harvesting end-point to the gate. The robot harvester inputs have been chosen based on the current maximum working width of Robotti, i.e., 3 metres, and operational speeds of 1.39 m s^{-1} that are both reachable by Robotti and by modern harvesters from a conservative point of view. As the crop yield has been assumed to be uniform across the fields, the threshing capacity will not be altered, and therefore the working speed can be kept constant. Additionally, it is needed to be mentioned that Robotti can perform "zero turn" manoeuvres, i.e., spin about a stationary point, and the plans include this manoeuvre in the paths for connecting rows.

2.2. Set of Fields Selection

A set of fields was generated from the latest national list of agricultural fields from the Danish Agricultural Agency (LBST) from the Ministry of Food, Agriculture and fisheries of Denmark [49]. A few steps were required to create the set of fields for this study: (a) from the original dataset from 2019, all the fields where cereals had been cultivated were selected; (b) all fields with registered obstacles inside the field were excluded; (c) based on the field complexity geometric feature found in [50], the 25% most complicated fields were removed; (d) the fields were evenly distributed in three groups based on their area, so that the group of smallest fields, i.e., smaller than 2.95 hectares, was discarded; and (e) in the final step, 20 fields were randomly selected for the medium and largest fields, i.e., 10 fields larger than 2.95 and smaller than seven hectares for the medium category, and 10 fields larger than seven hectares for the large category. The most complex fields and the fields with obstacles were excluded because their special geometry can increase the total harvest time per area [51], and consequently affect the study results. Additionally, the group of small fields was excluded because the produce of their high-quality areas is too small to harvest selectively. This is because, considering an average yield of 7.62 Mg ha^{-1} for winter wheat (*Triticum aestivum* L.), which is the most common grain crop in Denmark [52], and the chosen grain cart capacity of 10 Mg, a small sized field would not yield enough of the high-quality grain to even fill half a grain cart. An overview of the location of the resulting set of fields is shown in Figure 1.

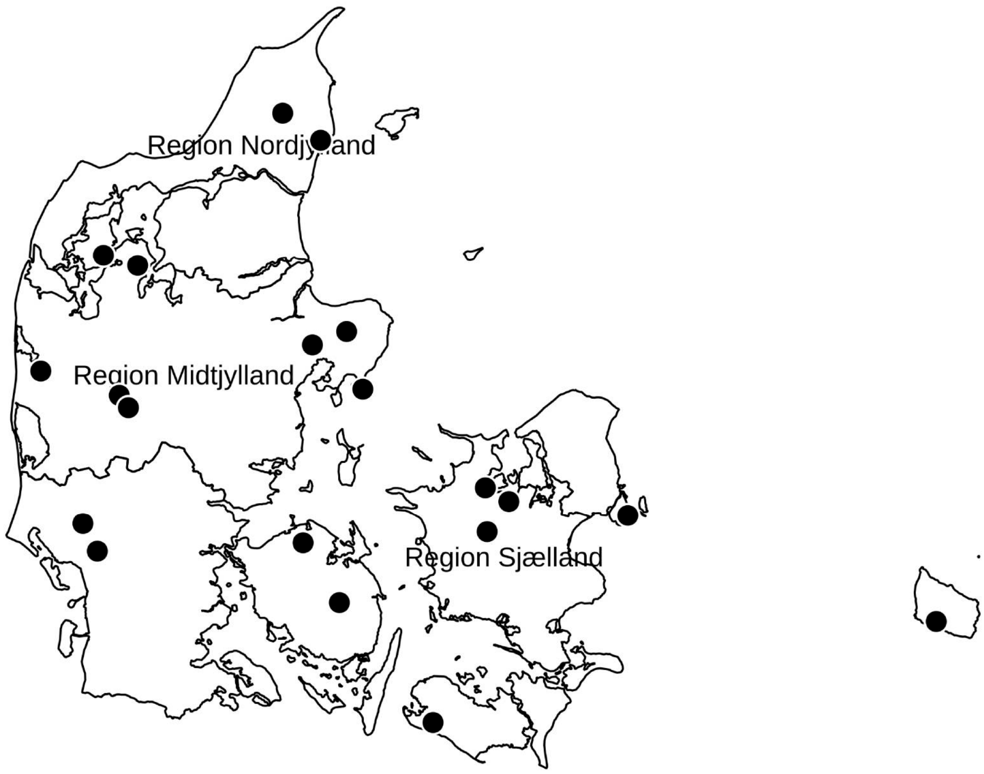

Figure 1. Spatial distribution of the selected set of fields across Denmark.

2.3. Quality Areas Creation

For this study, the high-quality areas were artificially created using the free and open-source Geographical Information System application QGIS v. 3.4.10, in order to provide a comparable set of data. In a real-world scenario, a quality map generated before the harvest operation would define the HQ areas to be harvested separately. It is implied that a reliable quality map can be created prior the harvest operation. For the comparative analysis three theoretical scenarios have been considered (Figure 2):

- Single edged case (SE): one HQ area situated at the edge of the field so that at least two of its sides collide with the boundary of the field. In this case, the HQ area could be considered a part-field or sub-field.
- Single in-field case (SI): the HQ area is collected into one bigger area inside the field.
- Twofold in-field case (TI): the HQ area is composed by two smaller areas inside the field.

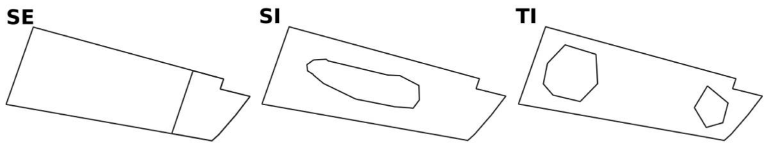

Figure 2. The three theoretical selective harvest scenarios studied in the paper shown for field M8 from the dataset. SE: single edged case; SI: single in-field case; and TI: twofold in-field case.

It has been designated that the HQ areas for the study should cover approximately 20% of the field total area. Smaller values than 20% would be too small to be harvested separately for a big part of the fields in the dataset. Additionally, higher values than 20% would make the in-field HQ areas, SI and TI, too big so that they would occupy most of the main field area, or would make them reach the field boundary, which goes against the definition of these scenarios. An overview of the set of fields and their hypothetical cases is presented in Figure 3 and Table 1.

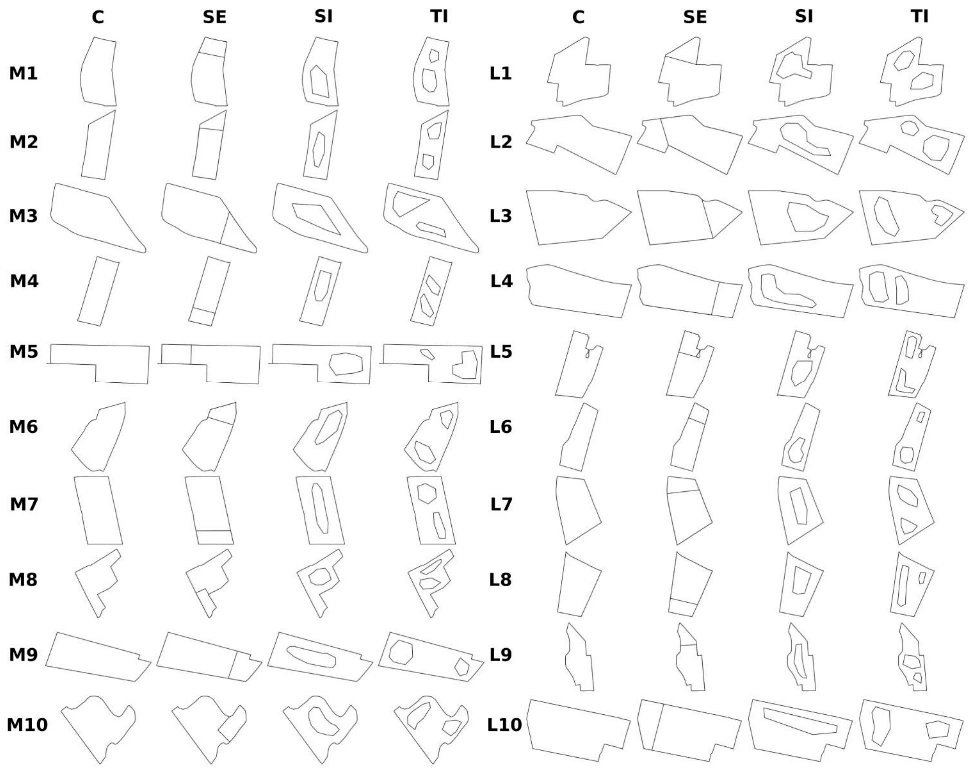

Figure 3. Overview of the set of fields and their distinct harvest cases.

Table 1. Field areas in hectares for the set of fields and the high-quality areas (HQ A) and remaining areas (Main A).

Field ID	Area A (ha)	SE		SI		TI		
		Main A	HQ A	Main A	HQ A	Main A	HQ A1	HQ A2
L1	8.45	6.83	1.61	6.72	1.72	6.75	0.80	0.89
L2	11.67	9.31	2.35	9.34	2.32	9.33	0.63	1.69
L3	8.98	7.17	1.80	7.15	1.82	7.16	1.24	0.57
L4	14.77	11.76	3.00	11.80	2.96	11.83	1.76	1.16
L5	8.56	6.77	1.79	6.84	1.72	6.83	0.78	0.95
L6	11.16	8.96	2.20	8.93	2.23	9.23	0.42	1.50
L7	7.03	5.57	1.45	5.62	1.40	5.61	0.87	0.54
L8	8.18	6.52	1.66	6.53	1.65	6.54	1.37	0.26
L9	32.29	25.82	6.46	25.83	6.46	25.84	4.75	1.68
L10	9.56	7.62	1.93	7.63	1.92	7.65	1.20	0.69
M1	2.96	2.37	0.59	2.34	0.62	2.41	0.14	0.41
M2	4.96	3.95	1.01	3.98	0.97	3.95	0.56	0.44
M3	6.55	5.24	1.31	5.23	1.31	5.23	0.94	0.36
M4	5.02	3.98	1.03	3.94	1.07	4.02	0.47	0.51
M5	5.46	4.38	1.08	4.33	1.13	4.38	0.13	0.94
M6	3.19	2.57	0.62	2.53	0.65	2.56	0.22	0.40
M7	6.18	4.95	1.22	4.94	1.23	4.94	0.72	0.51
M8	3.66	2.93	0.73	2.95	0.71	2.93	0.30	0.43
M9	6.83	5.44	1.39	5.49	1.33	5.46	0.99	0.37
M10	3.61	2.88	0.73	2.92	0.69	2.89	0.44	0.27

2.4. Virtual Capacity Analysis

The harvest capacity was calculated in estimated hectares per hour for each case scenario and for each field in the dataset. The capacity analysis was based on the simulated operational time of the robot harvester to complete the operation. The results were then compared against each other to determine significant differences between the hypothetical cases previously described. To achieve this, a *t*-Test was applied between the medium and large sized fields, between conventional and selective harvest, between the SE case and the SI and TI cases, as well as between the SI case and TI case. A significance level of 0.05 was used in the analysis.

2.5. Virtual Cost–Benefit Analysis

Along with the assumptions stated earlier, further assumptions for the cost–benefit analysis have been made: (a) the farm has the capabilities to store and sell the two different qualities of grain without directly implying additional costs; and (b) the total yield is the same in all scenarios studied for each field, so that the overall fuel consumption is only dependent on the harvest time. The cost–benefit analysis was determined by the operational costs to harvest each case scenario and field, and the benefits generated by selling the produce as a homogeneous product in conventional harvest or as high and lower qualities with corresponding prices. The operational costs per hour for the autonomous harvester robot have been estimated to be 800 DKK h^{-1} for the medium sized field and 650 DKK h^{-1} for the large sized fields, based on the current Robotti operating capacity and harvest contracting services prices in Denmark. The cost differences are due to field size affects harvest efficiency [53]. A grain cart cost during harvest has been estimated to be 600 DKK h^{-1}. The total field output has been assessed to be the average yield for winter wheat in Denmark from the last five years, i.e., 7.62 Mg ha^{-1} [52]. As 90% of the wheat produced in Denmark is for animal fodder [54], the prices used in the analysis correspond to fodder wheat. The average protein content for winter wheat in Denmark was 9.6% [55], which had an average price for 2020 of 1242 DKK Mg^{-1} [56]. The price premium for a protein content above 11% is 30 DKK in regard to values below 10% [57,58], resulting in a price of 1272 DKK Mg^{-1}. The economic return per hectare for the three SH cases studied compared to the conventional harvest case was calculated by $(\Delta HC + \Delta HR)/A_f$, where HC are the harvest costs in DKK, HR the harvest revenue of SH in DKK, and A_f the field area in hectares. The HC were calculated by adding the operational costs per hour of the autonomous harvester robot and the two grain carts, multiplied by the harvesting time for each field. The HR were calculated by multiplying the average yield by the field part area being harvested and by the corresponding grain prices.

3. Results

In total 160 harvesting simulations were successfully run so that the operational times for each of the fields and each of the quality areas of the four different scenarios could be analysed (Figures 3 and 4). Detailed harvest times and cost analysis for an example field, i.e., field L1 (Figure 4), are presented in Tables 2 and 3. The harvest times for SH increased compared to conventional harvest in all SH cases but one, i.e., field M8 for case SE that equalled the conventional harvest time (see Table 4). The harvesting times for the SH case SE increased between 0.0% and 15.9% compared to conventional harvest, having an average increase for the medium sized fields of 9.0% and 6.9% for the large sized fields. Case SI increased between 9.9% and 65.1% the harvest time in regard to conventional harvest, with an average of 30.8% and 24.4% for the medium and large sized fields, respectively. Case TI used between 11.6% and 72.6% more time than conventional harvest, spending in average 49.6% more time for medium sized fields and 34.1% for large sized fields (Table 4). Statistically significant differences were found between the harvest capacity of medium and large fields in all four cases (Table 5). Harvest capacities were also significantly different between conventional and all SH cases, as well as for SE compared to SI and TI cases. In the comparison between SI and TI SH cases, significant differences in harvest capacity were found for medium fields. However, no significant differences between harvest capacities were found between cases SI and TI among large fields (Table 5).

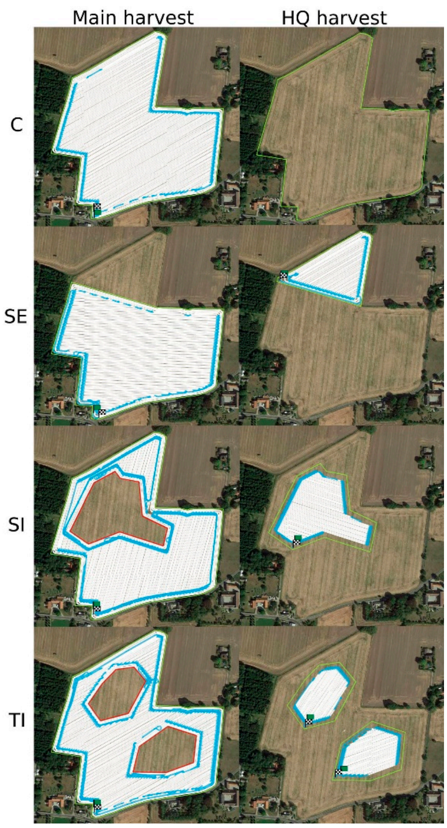

Figure 4. Route plans for field L1 for the four harvest cases, i.e., conventional (C), single edged case (SE), single in-field case (SI) and twofold in-field case (TI). White lines represent working paths and blue lines the connection paths.

Table 2. Detailed estimated harvest times in seconds of field L1 for the four harvesting cases and their field divisions.

Harvest Time (hours) for Field L1							
C	**SE**		**SI**		**TI**		
Main	**Main**	**HQ**	**Main**	**HQ**	**Main**	**HQ1**	**HQ2**
7.20	6.05	1.76	9.10	2.14	8.09	0.97	1.10

Table 3. Detailed calculations of harvest costs and revenues in DKK of field L1 for the four harvesting cases.

Field ID	Harvest Costs (DKK)				Harvest Revenues (DKK)			
	C	**SE**	**SI**	**TI**	**C**	**SE**	**SI**	**TI**
L1	−8100	−8852	−9744	−9626	80,001	80,371	80,396	80,391

Table 4. Estimated harvest times for the four harvesting cases and the percentage of time increase for the SH cases compared to conventional harvest.

Field ID	Harvest Time (hours) + Pct. Increase						
	C	**SE**		**SI**		**TI**	
L1	7.20	7.81	+8.4%	11.25	+56.1%	10.16	+41.0%
L2	9.51	9.71	+2.1%	11.80	+24.0%	12.32	+29.6%
L3	6.82	7.74	+13.5%	8.86	+29.8%	10.51	+54.0%
L4	10.71	11.44	+6.8%	13.29	+24.0%	13.84	+29.2%
L5	6.90	7.26	+5.2%	8.89	+28.9%	9.81	+42.2%
L6	8.95	9.63	+7.6%	10.99	+22.8%	9.31	+24.9%
L7	5.69	6.24	+9.7%	6.44	+13.2%	8.40	+47.7%
L8	6.80	7.29	+7.2%	8.30	+21.9%	8.38	+23.1%
L9	24.37	24.88	+2.1%	26.79	+9.9%	27.20	+11.6%
L10	7.70	8.11	+5.3%	8.75	+13.6%	10.59	+37.5%
M1	2.75	3.02	+9.9%	3.64	+32.7%	4.24	+54.4%
M2	4.07	4.72	+15.9%	5.00	+22.8%	6.13	+50.6%
M3	5.41	5.58	+3.2%	6.52	+20.6%	7.61	+40.6%
M4	4.06	4.49	+10.5%	5.15	+26.8%	6.30	+55.1%
M5	4.42	5.02	+13.6%	5.86	+32.4%	6.19	+40.1%
M6	2.81	3.16	+12.5%	4.63	+65.1%	4.84	+72.6%
M7	4.84	5.26	+8.8%	5.76	+19.1%	6.86	+41.8%
M8	3.71	3.71	+0.0%	4.85	+30.7%	5.71	+53.9%
M9	5.52	6.22	+12.8%	6.74	+22.1%	8.65	+56.9%
M10	3.68	3.78	+2.8%	4.97	+35.1%	4.77	+29.7%

The cost–benefit analysis shows that for seven out of the ten large fields there is an economic return between 5 and 36 DKK ha^{-1} for the SH SE case, while for the medium sized fields only three out of ten have a positive economic return for the SE case, which is between 24 and 46 DKK ha^{-1}. Cases SI and TI do not have any positive economic return in the results of this study. The SH case SE result in negative extra costs that range from −3 to −264 DKK ha^{-1} for the large fields and from −81 and −438 DKK ha^{-1} for the medium sized fields. The negative extra costs for harvesting selectively in case TI range from −11 to −221 DKK ha^{-1} for the large fields and between −211 and −496 DKK ha^{-1} for the medium sized fields (Table 6). Detailed harvest costs and revenues for an example field, i.e., field L1 (Figure 4), are presented in Table 3.

Table 5. Harvest capacities for the four harvesting cases studied and the field size groups, as well as *t*-test ($p > 0.05$) applied to the harvest capacities.

Harvest Case	Capacity Scores (Ha h^{-1})		*t*-Test for Harvest Capacity			
			Large vs. Medium	C vs. SH	SE vs. SI and TI	SI vs. TI
	$\bar{x}$	SD	*p*	*p*	*p*	*p*
Conventional	1.21	0.10				
Large	1.26	0.06	-	-		
Medium	1.16	0.10	0.026	-		
SE	1.12	0.09				
Large	1.18	0.07	-	0.015	-	
Medium	1.06	0.07	0.003	0.036	-	
SI	0.96	0.14				
Large	1.02	0.11	-	0.000	0.003	-
Medium	0.90	0.13	0.046	0.000	0.005	-
TI	0.87	0.15				
Large	0.97	0.13	-	0.000	0.000	0.172
Medium	0.78	0.09	0.002	0.000	0.000	0.038

Table 6. Total yields and economic returns for SH cases compared to conventional harvest.

Field ID	Yield (Mg)	Economic Return per Hectare (DKK ha^{-1})		
		SE	SI	TI
L1	64.41	−3	−264	−181
L2	88.93	35	−82	−111
L3	68.45	−21	−101	−221
L4	112.56	15	−67	−92
L5	65.29	21	−105	−175
L6	85.06	5	−73	−90
L7	53.58	−4	−23	−205
L8	62.40	8	−72	−79
L9	246.06	36	−3	−11
L10	72.85	19	−25	−151
M1	22.63	−32	−208	−385
M2	37.82	−64	−114	−307
M3	49.97	23	−98	−239
M4	38.26	−25	−135	−334
M5	41.67	−48	−176	−230
M6	24.37	−49	−438	−496
M7	47.12	−13	−81	−232
M8	27.94	46	−220	−418
M9	52.07	−41	−114	−344
M10	27.56	23	−259	−211

4. Discussion

Even though for one field, i.e., field M8, SH case SE presented no added harvest time (see Table 4), according to the results obtained SH affects significantly in all cases the harvest capacity when compared to conventional harvest (Table 5). This was an expected result as SH will in most cases increase the harvest time due to longer distances to be travelled. However, the results show that SH for some fields, e.g., Field M6 for case TI, it can increase the harvest time by more than 70% (see Table 4). Even if economically profitable, which it is not (see Table 6), this scenario would be unacceptable for most farmers, who are often greatly constrained by operational time schedules [59]. Field area also affects significantly the harvest capacity between conventional and SH, due to the field area effects on harvest efficiency [53]. Regarding the SH cases studied, no statistical difference was found in harvest capacity for HQ areas that cover 20% of the large fields when they are distributed inside the field in one (SI case) or two areas (TI case). This is considered to be caused by the large size of the fields compared to the 3-metre working width of the harvester, which makes it possible for the optimised route planner to reduce the connection paths by segmenting the field into subfields when optimising the route to follow. The SE case is considered to be the optimal SH scenario because it allows dividing the field into subfields to be managed and harvested separately. This is already sometimes being applied when thoughtful farmers manage a farm [60]. The SE case would also be easier to implement in contemporary farms without autonomous field robots. Even though the most complex fields were excluded when creating the field dataset (see Figure 3), field shape and the position as well as the shape of the HQ areas can have important effects on the total harvest times [61]. The shape and position of the HQ area(s) can mean an increased number of rows and the segmentation of the main field area into subfields (see Figure 4), which eventually increase the total harvest time (see Table 2) and consequently increase the harvesting costs (see Table 3). In some specific cases, SH was nearly as efficient as conventional harvest, while in other cases it increased the harvest time estimations in hours, above 50% more harvest time for many field cases (see field M6 in Table 4). Nonetheless, the theoretical SH cases presented here may not be the real cases encountered. The HQ areas modelled or measured for many fields can be scattered around the field and difficult to combine into HQ areas. A decision support system that evaluates harvesting times for different SH scenarios and prior harvest field tests for quality and quantity would aid the farm manager in decision making [20].

The harvest capacity results previously discussed need to be understood together with the cost–benefit analysis results, which show only minor positive revenues for some of the SE cases and greater losses for most fields in SI and TI cases. The little economic return resulting from the analysis of this study contrasts with the higher returns reported in other studies (e.g., [12,18–20]). Corresponding with 20 analyses, the modest or negative revenues found in this study are influenced by grain price differences and the operational and logistical costs of harvesting and managing these HQ areas separately. The grain price differences used in the other SH studies range from more than double to more than ten times higher than the grain price differences used in this study [1,12,18]. This affects the potential revenue of SH significantly. This can be caused by using in the analysis only fodder wheat price differences and not including premium prices for milling wheat. Including milling wheat prices in the comparison is not realistic in a Danish context as fodder grain cannot be destined for milling regardless of the protein content due to regulations. The man hour and machinery costs for harvesting in Denmark are also to be taken into account in the results, as they may be higher than in other contexts. Moreover, even if [20] included additional harvest distances in its operational cost calculations, none of the SH studies from literature have modelled the route planning time implications of SH that have been considered in this study. The additional times required for SH are an important factor to take into consideration because in some scenarios it can almost double the operational time. This study points out the necessity of including harvesting times in SH studies, which has not been included earlier in related work. It shows a contrasting reality for many scenarios compared to the results of related work—scenarios which farmers will often encounter in their fields. This study also uses a larger field dataset than the other studies related to SH, with the intention of addressing a larger variety of fields in regard to size and form. Consequently, the necessity to assess the implications of SH prior the operation is crucial, as shown by this study. Finally, it is needed for consideration that the robotic harvesting costs are based on current conventional harvest costs. However, robotic autonomous harvesting could potentially reduce the operational costs per hour, which would benefit the SH results.

Nonetheless, in order to address sustainability issues, such as import of alternative protein sources, SH can still result in economic revenue in some cases. From the results, it is observed that the SE cases suppose for many fields little additional time than conventional harvest. SE cases are also harvested significantly more efficiently than the other two cases. In addition, this type of harvesting method can also benefit management practices such as variable rate fertilizer application [11] that can enhance the output and more clearly define the HQ areas to be harvested separately.

In regard to the SH strategy followed by the autonomous harvester robot, the approach can also be applied to cases were harvesting lowest quality areas separately could increase the total average of the rest of the field to reach price premiums. A similar but alternative harvesting procedure could be harvesting the whole field simultaneously, but onload to different grain carts depending on the quality area the harvester is in. This would unavoidably require more grain carts involved in the operation as well as higher waiting times for them in the field with their subsequent costs, but could potentially reduce operation time compared to the method presented in this study.

Even though optimised route planning reduces the risk of a negative impact of wheel traffic in the soil [62], it is necessary to mention that the SH strategy presented in this paper will inevitably increase the infield traffic, which can have consequent negative impacts on future crop yields [63–65]. The selection of assumptions made in this study were essential to make the results comparable. However, some assumptions may not fully represent the reality in many fields, e.g., uniform yield distribution, and some could inevitably affect the results, e.g., distance to storage. Not all farms have the capabilities of storing and selling different grain qualities, which is indispensable for SH. Distance to storage from the field will unavoidably affect the results, as they may require to increasing the amount on grain carts or imply waiting times inside the field, which will automatically increase operational costs. This selected assumption represents an ideal but realistic scenario and is necessary for making the results comparable, as large distances will always affect negatively the economic return of the field [66]. A 20% HQ area is also an assumption that will affect the results if changed. Larger HQ areas will automatically improve the economic return of SH due to higher HQ yields, and the HQ areas would potentially reach the field boundary becoming the SE scenario, which has been proven to be harvested significantly more efficiently. Smaller HQ areas will predictably provide worse results for SH. Within the field, a uniformly distributed yield that has been assumed in this study to make a comparable dataset does not represent the reality of field crop yields. Within-field yield variations are a fact acknowledged by farmers and in literature (e.g., [67,68]). Furthermore, the long-recognised significant inverse relationship between yield and protein content [69,70] implies that the HQ areas will have a lower yield than the rest of the field, affecting the harvesting speed and fuel consumption because of differences in feeding rates and threshing power requirements [71]. Lower yields for the HQ areas would inevitably reduce the already marginal benefits and losses of selectively harvesting fodder winter wheat studied in this article in a Danish context. Another aspect to grain quality variability is the variability that is not captured by spatial quality maps [41], i.e., the variability within the mapping resolution, within the working width of the harvester or even within the grain spike. For addressing this variability, only grain segregation during harvest or after harvest can accomplish the task. However, this strategy relies on sensors that are very challenging to monitor the grain stream and a diverter valve that needs to react fast enough to segregate the grains. This is a task that cannot be relied upon with the current technological development state. These selected assumptions in the study intend to simulate realistic farm scenarios or are required to make the results comparable. The results with the given assumptions still provide an insight of SH applied to a Danish context in general. For a specific field, it is always recommended to make a pre-harvest assessment to study the feasibility of SH, which may be profitable in certain cases.

In different contexts, where the grain price differences are higher and the harvesting costs lower than in Denmark, SH can be an interesting option to feasibly increase the economic return of some fields. The ideal position of the HQ areas for higher economic returns is represented by case SE, where the edges of one HQ area reach the field boundary and cover at least 20% of the field area, creating a minimum reduced operational efficiency. In those scenarios, SH is expected to be feasible. Nonetheless, it is always required to study each field based on reliable grain quality maps to assess the viability of SH for that field.

Further research is required to address the potential benefits of SH with autonomous agricultural robots, where the route planning actively involves the grain carts so that the whole field is harvested in one go, but the grain carts are assigned to the harvester depending on the grain quality area they are located in. The influence of grain price differences and harvesting costs should be addressed too, as they truly determine the economical return of SH. Finally, the influence of the size, shape and location of the HQ areas with respect to the field boundary could be interesting to study as the results presented in this article show how much HQ area location and distribution affect the harvest capacity.

5. Conclusions

Selective harvesting has been studied for an autonomous agricultural robot in a Danish context for harvesting fodder winter wheat and for its potential to reduce the amount of imported alternative protein sources. The optimized route planning tool from the autonomous field robot, Robotti, employed in this study was able to generate routes for all the fields and cases of the dataset. Taking into consideration the selected assumptions, selective harvesting by harvesting separately high-quality areas (based on protein content) from the rest of the field is not economically feasible in a Danish context. The results showed significant differences in harvest capacity between conventional and selective harvest. The field shape as well as the location, shape and distribution of the high-quality area(s) had a significant influence on the SH capacity. These negative results for SH were affected by the small price differences of fodder wheat regarding protein content considered in this study. The high harvesting costs considered in the simulations had an influence too. In different contexts with higher grain price differences and lower harvesting costs, SH is expected to be economically feasible for the case SE, where the HQ areas reach the field boundaries and cover at least 20% of the field area. Additional research on the influence of grain price differences as well as harvesting costs, on the specific influence of shape and location of the HQ areas, and different route planning strategies will provide improved insight into the possibilities of SH performed by autonomous field robots.

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References

1. Farquharson, R.J. Production Response and Input Demand in Decision Making: Nitrogen Fertilizer and Wheat Growers. *Australas. Agribus. Rev.* **2006**, *14*, 5. [CrossRef]
2. Styczen, M.E.; Abrahamsen, P.; Hansen, S.; Knudsen, L. Analysis of the Signi Fi Cant Drop in Protein Content in Danish Grain Crops from 1990–2015 Based on N-Response in Fertilizer Trials. *Eur. J. Agron.* **2020**, *115*, 126013. [CrossRef]
3. Punia, S.; Singh, K.; Kumar, A. Difference in Protein Content of Wheat (*Triticum Aestivum* L.): Effect on Functional, Pasting, Color and Antioxidant Properties. *J. Saudi Soc. Agric. Sci.* **2019**, *18*, 378–384. [CrossRef]

4. Richards, P.D.; Myers, R.J.; Swinton, S.M.; Walker, R.T. Exchange Rates, Soybean Supply Response, and Deforestation in South America. *Glob. Environ. Chang.* **2012**, *22*, 454–462. [CrossRef]
5. Pelletier, N. Environmental Performance in the US Broiler Poultry Sector: Life Cycle Energy Use and Greenhouse Gas, Ozone Depleting, Acidifying and Eutrophying Emissions. *Agric. Syst.* **2008**, *98*, 67–73. [CrossRef]
6. Havlin, J.L.; Heiniger, R.W. A Variable-Rate Decision Support Tool. *Precis. Agric.* **2009**, *10*, 356–369. [CrossRef]
7. Pronin, D.; Börner, A.; Weber, H.; Scherf, K.A. Wheat (*Triticum Aestivum* L.) Breeding from 1891 to 2010 Contributed to Increasing Yield and Glutenin Contents but Decreasing Protein and Gliadin Contents. *J. Agric. Food Chem.* **2020**, *68*, 13247–13256. [CrossRef]
8. Fronzek, S.; Pirttioja, N.; Carter, T.R.; Bindi, M.; Ho, H.; Palosuo, T.; Ruiz-ramos, M.; Tao, F.; Trnka, M.; Acutis, M.; et al. Classifying Multi-Model Wheat Yield Impact Response Surfaces Showing Sensitivity to Temperature and Precipitation Change. *Agric. Syst.* **2018**, *159*, 209–224. [CrossRef]
9. Basso, B.; Cammarano, D.; Chen, D.; Cafiero, G.; Amato, M.; Bitella, G.; Rossi, R.; Basso, F. Landscape Position and Precipitation Effects on Spatial Variability of Wheat Yield and Grain Protein in Southern. *J. Agron. Crop Sci.* **2009**, *195*, 301–312. [CrossRef]
10. Godwin, R.J.; Miller, P.C.H. A Review of the Technologies for Mapping Within-Field Variability. *Biosyst. Eng.* **2003**, *84*, 393–407. [CrossRef]
11. Guerrero, A.; De Neve, S.; Mouazen, A.M. Data Fusion Approach for Map-Based Variable-Rate Nitrogen Fertilization in Barley and Wheat. *Soil Tillage Res.* **2021**, *205*, 104789. [CrossRef]
12. Whetton, R.L.; Waine, T.W.; Mouazen, A.M. Evaluating Management Zone Maps for Variable Rate Fungicide Application and Selective Harvest. *Comput. Electron. Agric.* **2018**, *153*, 202–212. [CrossRef]
13. Czechlowski, M.; Wojciechowski, T. The Utilization of Information about Local Variable Environmental Conditions to Predict the Quality of Wheat Grain during the Harvest. *J. Res. Appl. Agric. Eng.* **2013**, *58*, 31–34.
14. Peets, S.; Mounem, A.; Blackburn, K.; Kuang, B.; Wiebensohn, J. Methods and Procedures for Automatic Collection and Management of Data Acquired from On-the-Go Sensors with Application to on-the-Go Soil Sensors. *Comput. Electron. Agric.* **2012**, *81*, 104–112. [CrossRef]
15. Christensen, S.; Søgaard, H.T.; Kudsk, P.; Nørremark, M.; Lund, I.; Nadimi, E.S.; Jørgensen, R. Site-Specific Weed Control Technologies. *Weed Res.* **2009**, *49*, 233–241. [CrossRef]
16. Risius, H.; Hahn, J.; Huth, M.; Tölle, R.; Korte, H. In-Line Estimation of Falling Number Using near-Infrared Diffuse Reflectance Spectroscopy on a Combine Harvester. *Precis. Agric.* **2015**, *16*, 261–274. [CrossRef]
17. Long, D.S.; Mccallum, J.D.; Scharf, P.A. Optical-Mechanical System for On-Combine Segregation of Wheat by Grain Protein Concentration. *Agron. J.* **2013**, *105*, 1529–1535. [CrossRef]
18. Martin, C.T.; Mccallum, J.D.; Long, D.S. A Web-Based Calculator for Estimating the Profit Potential of Grain Segregation by Protein Concentration. *Agron. J.* **2013**, *105*, 721–726. [CrossRef]
19. Meyer-Aurich, A.; Gandorfer, M.; Weersink, A.; Wagner, P. Economic Analysis of Site-Specific Wheat Management with Respect to Grain Quality and Separation of the Different Quality Fractions. In Proceedings of the 12th Congress of European Association of Agricultural Economists—EAAE 2008, Ghent, Belgium, 26–29 August 2008; pp. 1–7. [CrossRef]
20. Tozer, P.R.; Isbister, B.J. Is It Economically Feasible to Harvest by Management Zone? *Precis. Agric.* **2007**, *8*, 151–159. [CrossRef]
21. Risius, H.; Hahn, J.; Korte, H. Near Infrared Spectroscopy for Sorting Grain According to Specified Quality Parameters on a Combine Harvester. In Proceedings of the Book of Abstracts XVII.th World Congress of the International Commission of Agricultural and Biosystems Engineering (CIGR | SCGAB), Québec, QC, Canada, 13–17 June 2010; p. 28.
22. Niedbała, G.; Czechlowski, M.; Wojciechowski, T. The Use of Artificial Neural Networks to Predict the Spatial Variability of Grain Quality during Combine Harvest of Wheat. *J. Res. Appl. Agric. Eng.* **2013**, *58*, 126–129.
23. Wojciechowski, T.; Niedbala, G.; Czechlowski, M.; Rudowicz, J.; Piechnik, L.; Niemann, J. Rapeseed Seeds Quality Classification with Usage of VIS-NIR Fiber Optic Probe and Artificial Neural Networks. In Proceedings of the 2016 International Conference on Optoelectronics and Image Processing, Warsaw, Poland, 10–12 June 2016; pp. 44–48.
24. Bonfil, D.J.; Mufradi, I.; Asido, S.; Long, D.S. On-Combine near Infrared Spectroscopy Applied to Prediction of Grain Test Weight. In Proceedings of the 9th International Conference on Precision Agriculture, Denver, CO, USA, 20–23 July 2008; pp. 1–8.
25. Villa-Henriksen, A.; Edwards, G.T.C.; Pesonen, L.A.; Green, O.; Sørensen, C.G. Internet of Things in Arable Farming: Implementation, Applications, Challenges and Potential. *Biosyst. Eng.* **2020**, *191*, 60–84. [CrossRef]
26. Ren, D.; Martynenko, A. Guest Editorial: Robotics and Automation in Agriculture. *Int. J. Robot. Autom.* **2018**, *206*, 1–5. [CrossRef]
27. Bechar, A.; Vigneault, C. Agricultural Robots for Field Operations: Concepts and Components. *Biosyst. Eng.* **2016**, *149*, 94–111. [CrossRef]
28. Kayacan, E.; Kayacan, E.; Ramon, H.; Saeys, W. Towards Agrobots: Identification of the Yaw Dynamics and Trajectory Tracking of an Autonomous Tractor. *Comput. Electron. Agric.* **2015**, *115*, 78–87. [CrossRef]
29. Moysiadis, V.; Tsolakis, N.; Katikaridis, D.; Sørensen, C.G.; Pearson, S.; Bochtis, D. Mobile Robotics in Agricultural Operations: A Narrative Review on Planning Aspects. *Appl. Sci.* **2020**, *10*, 3453. [CrossRef]
30. Araújo, S.O.; Peres, R.S.; Barata, J.; Lidon, F.; Ramalho, J.C. Characterising the Agriculture 4.0 Landscape—Emerging Trends, Challenges and Opportunities. *Agron. J.* **2021**, *11*, 667. [CrossRef]

31. Villa-Henriksen, A.; Skou-Nielsen, N.; Sørensen, C.A.G.; Green, O.; Edwards, G.T.C. Internet-Based Harvest Fleet Logistic Optimisation. In Proceedings of the European Agricultural Conference, Wageningen, The Netherlands, 8–12 July 2018; Groot Koerkamp, P.W.G., Lokhorst, C., Ipema, A.H., Kempenaar, C., Groenestein, C.M., van Oostrum, C.G., Ros, N.J., Eds.; Wageningen University and Research: Wageningen, The Netherlands, 2018; pp. 56–61. [CrossRef]
32. Edwards, G.T.C.; Hinge, J.; Skou-Nielsen, N.; Villa-Henriksen, A.; Sørensen, C.A.G.; Green, O. Route Planning Evaluation of a Prototype Optimised Infield Route Planner for Neutral Material Flow Agricultural Operations. *Biosyst. Eng.* **2017**, *153*, 149–157. [CrossRef]
33. Seyyedhasani, H.; Dvorak, J.S. Using the Vehicle Routing Problem to Reduce Field Completion Times with Multiple Machines. *Comput. Electron. Agric.* **2017**, *134*, 142–150. [CrossRef]
34. Busato, P.; Berruto, R.; Saunders, C. Optimal Field-Bin Locations and Harvest Patterns to Improve the Combine Field Capacity: Study with a Dynamic. In *CIOSTA 07 001*; The CIGR Ejournal; Agricultural Engineering International: Beijing, China, 2007; Volume IX.
35. Edwards, G.; Sørensen, C.G.; Bochtis, D.D.; Munkholm, L.J. Optimised Schedules for Sequential Agricultural Operations Using a Tabu Search Method. *Comput. Electron. Agric.* **2015**, *117*, 102–113. [CrossRef]
36. Jensen, M.A.F.; Bochtis, D.; Sorensen, C.G.; Blas, M.R.; Lykkegaard, K.L. In-Field and Inter-Field Path Planning for Agricultural Transport Units. *Comput. Ind. Eng.* **2012**, *63*, 1054–1061. [CrossRef]
37. Bochtis, D.D.; Sørensen, C.G.; Green, O. A DSS for Planning of Soil-Sensitive Field Operations. *Decis. Support Syst.* **2012**, *53*, 66–75. [CrossRef]
38. Gorter, N. *Route Optimization of Primary and Service Units in Agricultural Harvesting Operations*; Wageningen University and Research Centre: Wageningen, The Netherlands, 2019.
39. Joshi, N.; Baumann, M.; Ehammer, A.; Fensholt, R.; Grogan, K.; Hostert, P.; Jepsen, M.R.; Kuemmerle, T.; Meyfroidt, P.; Mitchard, E.T.A.; et al. A Review of the Application of Optical and Radar Remote Sensing Data Fusion to Land Use Mapping and Monitoring. *Remote Sens.* **2016**, *8*, 70. [CrossRef]
40. Gyldengren, J.G.; Abrahamsen, P.; Olesen, J.E.; Styczen, M.; Hansen, S.; Gislum, R. Effects of Winter Wheat N Status on Assimilate and N Partitioning in the Mechanistic Agroecosystem Model DAISY. *J. Agron. Crop Sci.* **2020**, *206*, 784–805. [CrossRef]
41. Leroux, C.; Tisseyre, B. How to Measure and Report Within-Field Variability: A Review of Common Indicators and Their Sensitivity. *Precis. Agric.* **2018**, *20*, 562–590. [CrossRef]
42. Palosuo, T.; Kersebaum, K.C.; Angulo, C.; Hlavinka, P.; Moriondo, M.; Olesen, J.E.; Patil, R.H.; Ruget, F.; Rumbaur, C.; Takáč, J.; et al. Simulation of Winter Wheat Yield and Its Variability in Different Climates of Europe: A Comparison of Eight Crop Growth Models. *Eur. J. Agron.* **2011**, *35*, 103–114. [CrossRef]
43. Parry, D.W.; Jenkinson, P.; McLeod, L. Fusarium Ear Blight (Scab) in Small Grain Cereals—A Review. *Plant Pathol.* **1995**, *44*, 207–238. [CrossRef]
44. Paul, P.A.; Lipps, P.E.; Madden, L.V. Relationship between Visual Estimates of Fusarium Head Blight Intensity and Deoxynivalenol Accumulation in Harvested Wheat Grain: A Meta-Analysis. *Phytopathology* **2005**, *95*, 1225–1236. [CrossRef] [PubMed]
45. FAO. *Global Food Losses and Food Waste—Extent, Causes and Prevention*; FAO: Rome, Italy, 2011. [CrossRef]
46. Green, O.; Schmidt, T.; Pietrzkowski, R.P.; Jensen, K.; Larsen, M.; Nyholm Jørgensen, R. Commercial Autonomous Agricultural Platform—Kongskilde Robotti. In Proceedings of the Second International Conference on Robotics, Associated High-Technologies and Equipment for Agriculture and Forestry—RHEA 2014: New Trends in Mobile Robotics, Perception and Actuation for Agriculture and Forestry, Madrid, Spain, 21–23 May 2014; pp. 351–356.
47. Foldager, F.F.; Balling, O.; Gamble, C.; Larsen, P.G.; Boel, M.; Green, O. Design Space Exploration in the Development of Agricultural Robots. In Proceedings of the EurAgEng 2018, Wageningen, The Netherlands, 8–12 July 2018; pp. 314–321.
48. AgroIntelli. Versatile and Autonomous Agricultural Robot Solving Multiple Tasks in the Field. Available online: https://www.agrointelli.com/robotti/ (accessed on 14 April 2021).
49. LBST. Markkort og Markblokke. Available online: https://lbst.dk/landbrug/kort-og-markblokke/markkort-og-markblokke/ (accessed on 16 March 2021).
50. Skou-Nielsen, N.; Villa-Henriksen, A.; Green, O.; Edwards, G.T.C. Creating a Statistically Representative Set of Danish Agricultural Fi Eld Shapes to Robustly Test Route Planning Algorithms. In *Precision Agriculture (ECPA) 2017, 8:2*; Cambridge University Press: Edinburgh, UK, 2017; pp. 615–619. [CrossRef]
51. Oksanen, T. Shape-Describing Indices for Agricultural Field Plots and Their Relationship to Operational Efficiency. *Comput. Electron. Agric.* **2013**, *98*, 252–259. [CrossRef]
52. LF, Landbrug og Fødevarer. *Fakta Om Fødevareklyngen 2020—Bæredygtig Udvikling*; Landbrug og Fødevarer: Copenhagen, Denmark, 2020.
53. Xangsayasane, P.; Phongchanmisai, S.; Bounphanousai, C.; Fukai, S. Combine Harvesting Efficiency as Affected by Rice Field Size and Other Factors and Its Implication for Adoption of Combine Contracting Service. *Plant Prod. Sci.* **2019**, *22*, 68–76. [CrossRef]
54. Jørgensen, J.R. Kvalitet Af Hvede Til Produktion Af Brød Og Andre Produkter. In *Produktion af Kvalitetshvede i Danmark, en Oversigt over Problemer og Muligheder*; DJF rapport Markbrug, No. 53; Waagepetersen, J., Petersen, J.B., Knudsen, L., Deneken, G., Jørgensen, J.R., Eds.; Danish Institute of Agricultural Sciences, Department of Plant Biology: Foulum, Denmark, 2001; pp. 25–32.
55. Sloth, N.M.; Poulsen, J. *Næringsindhold i Korn Fra Høsten 2020*; SEGES: Aarhus, Denmark, 2020.
56. SEGES. Farmtalonine. Available online: www.landbrugsinfo.dk (accessed on 12 May 2021).

57. DLG. DLG Belønner Igen Højere Proteinindhold i Korn. Available online: https://www.dlg.dk/Om-DLG/Presse/Nyheder/2017/03/DLG-beloenner-igen-hoejere-proteinindhold-i-korn (accessed on 12 May 2021).
58. VA. *Høstinformation 2020*; Vestjyllands Andel: Herning, Denmark, 2020.
59. Edwards, G.; Bochtis, D.; Søresen, C.G. Multi-Machine Coordination: Scheduling Operations Based on Readiness Criteria and Using a Modified Tabu Search Algorithm. *IFAC Proc. Vol.* **2013**, *4*, 191–195. [CrossRef]
60. SmartAgriHubs. *Valued Grain Chain—From Farm Perspective*; LUKE: Helsinki, Finland, 2021.
61. Spekken, M.; De Bruin, S. Maneuvering and Servicing Time. *Precis. Agric.* **2013**, *14*, 224–244. [CrossRef]
62. Villa-Henriksen, A.; Skou-Nielsen, N.; Munkholm, L.J.; Sørensen, C.A.G.; Green, O.; Edwards, G.T.C. Infield Optimized Route Planning in Harvesting Operations for Risk of Soil Compaction Reduction. *Soil Use Manag.* **2020**, *2020*, 1–12. [CrossRef]
63. Chamen, T. The Potential of Controlled Traffic Farming to Mitigate Greenhouse Gas Emissions and Enhance Carbon Sequestration in Arable Land: A Critical Review. *Trans. ASABE* **2015**, *58*, 707–731. [CrossRef]
64. Schjønning, P.; Lamandé, M.; Munkholm, L.J.; Lyngvig, H.S.; Nielsen, J.A. Soil Precompression Stress, Penetration Resistance and Crop Yields in Relation to Differently-Trafficked, Temperate-Region Sandy Loam Soils. *Soil Tillage Res.* **2016**, *163*, 298–308. [CrossRef]
65. Obour, P.B.; Keller, T.; Jensen, J.L.; Edwards, G.; Lamandé, M.; Watts, C.W.; Sørensen, C.G.; Munkholm, L.J. Soil Water Contents for Tillage: A Comparison of Approaches and Consequences for the Number of Workable Days. *Soil Tillage Res.* **2019**, *195*, 104384. [CrossRef]
66. Lamsal, K.; Jones, P.C.; Thomas, B.W. Computers & Industrial Engineering Harvest Logistics in Agricultural Systems with Multiple, Independent Producers and No on-Farm Storage. *Comput. Ind. Eng.* **2016**, *91*, 129–138. [CrossRef]
67. Lyle, G.; Bryan, B.A.; Ostendorf, B. Post-Processing Methods to Eliminate Erroneous Grain Yield Measurements: Review and Directions for Future Development. *Precis. Agric.* **2014**, *15*, 377–402. [CrossRef]
68. Ping, J.L.; Dobermann, A. Processing of Yield Map Data. *Precis. Agric.* **2005**, *6*, 193–212. [CrossRef]
69. Terman, G.L.; Ramig, R.E.; Dreier, A.F.; Olson, R.A. Yield-Protein Relationships in Wheat Grain, as Affected by Nitrogen and Water. *Agron. J.* **1969**, *61*, 755–759. [CrossRef]
70. Simmonds, N.W. The Relation Between Yield and Protein in Cereal Grain. *J. Sci. Food Agric.* **1995**, *76*, 309–315. [CrossRef]
71. Tieppo, R.C.; Romanelli, T.L.; Milan, M.; Sørensen, C.A.G.; Bochtis, D. Modeling Cost and Energy Demand in Agricultural Machinery Fl Eets for Soybean and Maize Cultivated Using a No-Tillage System. *Comput. Electron. Agric.* **2019**, *156*, 282–292. [CrossRef]