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# Land use optimization tool for sustainable intensification of high-latitude agricultural systems

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ABSTRACT

Recent studies assessing agricultural policies, including the EU's Agri-Environment Scheme, have shown that these have been successful in attaining some environmental goals. In Finland, however, the economic situation of farms has dramatically fallen and hence, the actions do not result in social acceptability. Sustainable intensification is a means to combine the three dimensions of sustainability: environmental, economic and social. Here we introduce a novel land use optimization and planning tool for the sustainable intensification of high-latitude agricultural systems. The main rationale for the development of the tool was to achieve a systematic and comprehensive conception for land allocation across Finland, where field parcels vary substantially in their conditions. The developed tool has a three-step scoring system based on seven physical characteristics (parcel size, shape, slope, distance to the farm center and waterways, soil type and logistic advantages) and the productivity of field parcels. The productivity estimates are based on vegetation indices derived from optical satellite data. The tool allocates virtually all > 1 million field parcels in Finland either to sustainable intensification, extensification or afforestation. The tool is dynamic in the sense that its boundary values for land allocation can be fixed according to changes in social targets and supporting policies. Additionally, it can be applied year after year by acknowledging new available data, *e.g.*, on vegetation indices and field parcel rearrangements between farms. Furthermore, it can be applied to all farm types and across Finland. It is a tool for land use planning, implementation and monitoring, but its thorough implementation calls for further development of policy instruments, which are currently more supportive towards land sharing than land sparing activities.

## 1. Introduction

Agriculture in Finland has swerved off the road of sustainable development when considering all the dimensions of sustainability, *i.e.*, the economic and social dimensions in addition to environmental sustainability (Peltonen-Sainio et al., 2015b, 2016a). Undesirable shifts in the socio-economic conditions in high-latitude agriculture have been driven by changes in policy, markets and prices since Finland joined European Union in 1995. The minimization of costs has been the primary response of the farmers trying to navigate the emerging economic challenges caused by reductions in cereal prices with concomitant increases in fertilizer, energy and labour costs (Niemi and Ahlstedt, 2014). The use of inputs and resources has not only declined *per se* but their use has been "averaged" across agricultural land without sufficiently considering differences between field parcels in their physical characteristics, productivity and responsiveness to input use. Such an operational model does a disservice to sustainability when it ignores the need for more inputs of highly productive, responsive fields parcels, while it often overdoses the allocation of inputs to poorly performing fields (Peltonen-Sainio et al., 2015b).

The planning and management of agricultural systems – with many expectations from both producer and society – are complex and dependent on biological and socio-economic conditions in a region (Dogliotti et al., 2014b). Acknowledging such conditions is crucial when developing tools to support farmers' decision-making. Recently, a number of design-support tools, models and methodologies, *e.g.* for

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multi-stage, multi-objective and multi-criteria optimization of land use have been developed to meet various aims. For example, land use planning tools and models support the optimization of: a) crop sequencing and allocation to maximize farmers' profits while fulfilling the basic requirements set to enhance biodiversity and preserve soil quality (Galán-Martín et al., 2015; Capitanescu et al., 2017); b) the allocation of land and water resources to maximize productivity and minimize soil erosion and other environmental problems (Gao et al., 2010; Galán-Martín et al., 2017; Singh, 2017); c) planning land use changes by acknowledging their impacts and trade-offs with nature conservation and ecosystem services (Groot et al., 2007; Kennedy et al., 2016; Groot et al., 2018); and d) land use and management to foster adaptation to climate change (Klein et al., 2013). Already quite modest modifications to farming practices may considerably increase farm performance when measured with various indicators (Groot et al., 2012). As climatic and socio-economic conditions steer land use planning (Dogliotti et al., 2014a), developed tools often acknowledge the conditions of a certain region, though the method as such may also be applicable elsewhere. Success in developing a tool and implementing it to meet the real-world challenges related to land use planning and optimization (Seppelt et al., 2013) call for a participatory approach and the entrance of farmers, advisers, policy makers and other relevant stakeholders into the planning and development processes (Le Gal et al., 2011; Kaim et al., 2018), as well as their participation in reviewing the outcomes (Cotter et al., 2014).

Recent studies assessing the impacts of EU policies, especially the Agri-Environment Scheme (AES), have revealed declining trends in yields, quality and productivity in Finnish agriculture (Peltonen-Sainio et al., 2015b, 2016a). Therefore, major changes are needed to combine environmental, economic and social sustainability in the future (Soussana et al., 2012). Sustainable intensification is the means to combine all these three dimensions of sustainability (Gadanakis et al., 2015; Bretagnolle et al., 2018). Land sparing as a measure of sustainable intensification actions usually means further enhancement of yields in intensive arable landscapes and allows the removal of some land from agricultural production and sparing it for nature. Land sharing, on the other hand, refers to large-scale, low-intensive land use (Law and Wilson, 2015) and hence, only negligible agricultural land areas remain untouched. Our land use optimization approach follows the basic idea of land sparing, whereas the current agriculture in Finland resembles the land sharing course.

We introduce a land use optimization tool, based on an a priori method (Kaim et al., 2018), meaning that the used algorithms are largely based on an outcome of a process where farmers' decision-making behaviour was "phenotyped" and applied (Peltonen-Sainio et al., 2017, 2018). Such a tool is necessary because decision making is a challenging process not least due to the high number of interacting and sometimes conflicting factors and conditions that need to be acknowledged and prioritized, and farmers do not have sufficient and exact information for their decision making. Therefore, we developed a tool to examine large-scale land use changes as a part of the sustainable intensification of agricultural systems in Finland. This tool enables dynamic land use changes over time, *i.e.*, shifts from extensification to intensification and *vice versa*. The tool also indicates the land area that should be removed from agricultural production for afforestation, which again is an irreversible decision for a farmer. Finland is well justified as a testbed for such a national-scale, novel scheme due to the high variability in field parcel characteristics, as well as variable growing conditions, yield and quality of harvested crops, as well as the environmental vulnerability depending on region (Peltonen-Sainio and Jauhiainen, 2014; Peltonen-Sainio et al., 2016b). Furthermore, Finnish crop rotations suffer from cereal and even cereal species monocultures and thereby, a lack of diversity (Peltonen-Sainio et al., 2017). Land use changes implemented by utilizing the land use optimization tool introduced here may facilitate improvements not only on a farm scale but also on a landscape scale and may enhance biodiversity (Piha et al., 2007; Herzon et al., 2011; Ekroos et al., 2013), reduce greenhouse gas (GHG) emissions especially as peatlands are targeted for afforestation (Regina et al., 2016), and alleviate the risk of nutrient leaching (Puustinen et al., 2010), which all need to be monitored in the next phase.

The development of the land use optimization tool called for a detailed understanding of the variation in productivity and physical characteristics on the field parcel scale, as these conditions are important drivers for land allocation and land use changes. Furthermore, to achieve systematic assessment, scoring, implementation and monitoring of future land use changes, differences depending on the farm type and farm size need to be acknowledged. The aim of this study was to develop a land use optimization tool, which considers 1) numerous physical field parcel characteristics that are critical for land allocation, and furthermore, 2) combine this information with optical spectrum satellite data based on Normalized Difference Vegetation Index (NDVI) -values to enable the assessment of productivity differences between field parcels. The ultimate aim is to facilitate the future sustainable intensification of high-latitude agricultural systems by classifying field parcels as either sustainably intensified, extensified or afforested fields. Sustainably intensified fields form the main field capital of a farm and are primarily used for food production, while extensified fields are allocated for greening purposes (green fallow, nature managed fields, game fields *etc.*) to increase landscape diversity and recover from soil compaction or any other imperfections. Afforested fields again have too many serious defects and therefore, lack any future role for food security.

## 2. Materials and methods

The land use optimization tool was developed to include three scoring rounds that provide traffic lights in each step of the scoring process. The first scoring round is based on the general physical characteristics of field parcels and the second round is based on productivity estimations that are calibrated using optical satellite NDVI-values estimated for each parcel and also on the proximity to waterways. The final third scoring round again focusses on the soil type, especially on organic peat soils, and on the logistic advantages for field operations. Economic aspects were indirectly included into the tool by considering *e.g.*, field size, shape and productivity, distance to farm center, and also logistic advantages in the final stage of field parcel disposition, while environmental aspects were included by acknowledging field slope, proximity to waterways and soil type.

### 2.1. *General physical characteristics of field parcels used for the 1st scoring round*

Data from the Agency of Rural Affairs (Mavi) from 2011 to 2015 was used to assess the physical field parcel characteristics, the size of the field parcel (ha), the distance of a field parcel from the farm centre (m) divided by the farm size in hectares and the field shape and slope (%). During the first step of the land use allocation process, all four physical characteristics were proportioned to their medians and thereafter, additional characteristic-specific coefficients were used: the coefficient was dependent on how relevant the characteristic was to the farmers' land allocation decision (Peltonen-Sainio et al., 2018). A multinomial logistic regression analysis was carried out to model the probability of the allocation of field parcels for different crops. This analysis was based on 64,744 field parcels: if the probability was low for the allocation of the field parcel to non-productive greening crops, the physical characteristics of the field parcel were considered to be good and *vice versa*. The general form of the model was: $\log(p/(1\text{-}p)) = \mu + \boldsymbol{x}\beta$. Because the relationship between $\log(p/(1\text{-}p))$ and different physical field parcel characteristics $\boldsymbol{x} = (x_1\ x_2\ x_3\ x_4)$ was not linear, different characteristics were categorized in the original analysis (Peltonen-Sainio et al., 2018). To achieve continuous scoring, a brokenline approximation was carried out for estimated values of β:

$$x_{i1}\beta = \begin{cases} -1.1 + 0.38x_{i1}, & where\ x_{i1} \le 10ha \\ 2.7, & where\ x_{i1} > 10ha \end{cases}$$

where $x_{i1}$ is the size of the ith field parcel.

$$x_{i2}\beta = \begin{cases} 0.4000 - 0.000600x_{i2} & , when\ 0m < x_{i2} \le 500m \\ 0.1363 - 0.000073x_{i2} & , when\ 500m < x_{i2} \le 10000m, \\ -0.5937 & , when\ x_{i2} > 10000m \end{cases}$$

where $x_{i2}$ is the distance from the farm center.

$$x_{i3}\beta = \begin{cases} 0.2 - 0.02x_{i3} & , when\ 0.0° < x_{i3} \le 2.5° \\ 0.3 - 0.06x_{i3} & , when\ 2.5° < x_{i3} \le 5.0° \\ 0.5 - 0.10x_{i3} & , when\ 5.0° < x_{i3} \le 18.0° \\ 2.81 - 0.229x_{i3} & , when\ 18.0° < x_{i3} \le 28.0° \end{cases}$$

,where xi3 is the slope of the ith field parcel.

$$x_{i4}\beta = \begin{cases} -1.2 + 2.9x_{i4} & , when\ 0.0 < x_{i4} \le 0.4 \\ -0.52 + 1.2x_{i4} & , when\ 0.4 < x_{i4} \le 0.6, \\ -0.25 + 0.75x_{i4} & , when\ 0.6 < x_{i4} \le 1.3 \end{cases}$$

where $x_{i4}$ is the shape of the ith field parcel [= the area of field / (the length of the boundaries of the field / 4)$^2$; *i.e.*, the shape is 1.00 for a square field]. The maximum value of the shape is 4/π = 1.27324.

According to the original logistic regression analysis, μ = 0.426. Additionally, from the general form of the logistic regression equation, p = exp(μ + xβ)/(1 + exp(μ + xβ)). Next, p was used as the 1st scoring item and all the scores were between 0 and 1. If the 1st score was ≥0.55 then the field was defined as “green” (sustainable intensification), if again 0.40 ≤ 1st score < 0.55 the field was defined as “yellow” (uncertain whether sustainably intensified or extensified), 0.30 ≤ 1st score < 0.40 as “red” (extensification) and 0.00 ≤ 1st score < 0.30 as “dark red” (afforestation).

### 2.2. Productivity and proximity to waterways used for the 2nd scoring round

#### 2.2.1. Satellite imagery and derived NDVI-values

After the first scoring according to the general physical characteristics of the field parcels, the production capacity was assessed by using satellite data for different crops from critical growth stages to determine the total biomass and yield. Scoring was done on three preselected dates between the 1st of July and 10th of August. Dates were selected separately for each sub-area to minimize the cloud cover over the study area. For grasslands, three dates were selected between the 10th of May and 10th of June. In Finland, the first cut is typically done between the 15th and 25th of June and the NDVI-values for perennial grasses are mutually comparable only before that. The different crops included in the assessment were spring barley (*Hordeum vulgare* L.), oats (*Avena sativa* L.) and wheat (*Triticum aestivum* L.), spring rapeseed (both *Brassica rapa* L. and *B. napus* L.), winter wheat and rye (*Secale cereale* L.), peas (*Pisum sativum* L.) and faba beans (*Vicia faba* L.), as well as perennial grasslands.

NDVI was used to characterize the differences in the productivity of the field parcels. NDVI is a numerical band combination ratio of RED and Near Infrared (NIR) reflectance extracted from optical satellite imagery. The calibrated and scaled NDVI-values for different agricultural crops indicate photosynthetic activity in different vegetative and generative development stages. NDVI estimation has been widely used previously in Earth remote sensing campaigns to monitor large area changes in biomass and crop yields in EU countries (Gobron et al., 2006).

Data from two satellite systems was used in this study. From 2011 until 2015 data was provided by NASA through the Landsat 7 and 8 missions. For 2016 and 2017 data from ESA’s Sentinel-2 mission was used (Drusch et al., 2012). The Landsat data products were downloaded from the service of the U.S. Geological Survey [https://earthexplorer.usgs.gov/]. In regards to the NDVI values, both Landsat and Sentinel-2 provide similar multispectral image bands in the optical and near-infrared region. Sentinel-2 has slightly better spatial resolution, which makes it easier to use in mapping NDVI variations within parcels, however, it does not affect the parcel averaged NDVI values.

In the calculation of the parcel specific NDVI attributes, the Land Parcel Identification System (LPIS) was used. LPIS is a digitized agricultural land parcel database maintained by the Finnish agency for rural affairs (Mavi) and it contains over 1.2 million field parcels in Finland. The derivation of averaged NDVI values per field parcel was done with a similar processing chain to the atmospherically corrected Landsat and Sentinel-2 data products. The Landsat data was processed manually using Esri ArcGIS and QuantumGIS (Geographical Information System) software. The Sentinel-2 data was processed automatically by utilizing the Earth Observation processing toolkit developed at FGI (for more details see (Wittke et al., 2019)). Only cloud-masked products with less than 30% cloud cover for the Landsat data (2011–2015) and less than 99% cloud cover per tile for the Sentinel-2 data (2016–2017) during the growing season over Finland were used.

First, geo-corrected NDVI raster images were calculated using the red and NIR band values (Table 1). The NDVI values were then intersected with the LPIS land parcels of the 20 pilot farms (and cloud-masked for Sentinel-2). The mean NDVI values within the parcels were stored in a standard csv file format for further analysis. Real data on specific crop rotations as well as soil data for different crops was also added to the file. Then, the NDVI values calculated from the satellite images were phenologically reclassified using the SatPhenClass algorithm (Laurila et al., 2010a, b). The phenological phases of phenB and phenC correspond to the vegetative and generative developmental phases of the studied crops, *i.e.* phases that are especially critical for determining productivity.

For this study, the satellite data sources were not combined, but used individually in the selected time windows. Even though data from separate satellite systems was used in this study, differences in the ground resolution (30 m for Landsat and 10 m for Sentinel-2) and band wavelength intervals did not show a detectable bias in the extracted NDVI values per parcel in visual inspection. This was due to the averaging over the parcels and high band overlap of the bands required for NDVI calculation. Therefore, the satellite data was considered to be sufficiently accurate for the analysis considering the variations within class present in other data sources. Comparisons of different field parcels within same area were made separately for all years. This finally eliminates possible bias caused by two different satellites.

#### 2.2.2. Estimating productivity gap and acknowledging proximity to waterways

By following the procedure described above more than 1,300,000 NDVI-values were compiled. The Landsat data covered several regions of Finland, while the Sentinel 2 data was from Southwest Finland. The data was then used to analyze the productivity of the field parcels. Finland was divided into 20 regions because there were clear differences between NDVI-values of different regions. The productivity gap

**Table 1**
Satellite platforms whose data were used in NDVI calculations, the used spectral bands and their spatial resolution on ground.

| Satellite platform | Year | Band number | Band central wavelength (nm) | Bandwidth (nm) | Ground resolution (m) |
|---|---|---|---|---|---|
| Landsat 7 | 2011 – | 3 (red) | 660.0 | 60 | 30 |
| | 2013 | 4 (NIR) | 835.0 | 130 | 30 |
| Landsat 8 | 2014 – | 4 (red) | 654.5 | 37 | 30 |
| | 2015 | 5 (NIR) | 865.0 | 28 | 30 |
| Sentinel-2 | 2016 – | 4 (red) | 664.6 | 38 | 10 |
| | 2017 | 8 (NIR) | 832.8 | 145 | 10 |

was calculated as:

$$gap_i = \begin{cases} 0, & if\ x_i \geq g_{90} \\ a + bx_i, & if\ g_{90} < x_i \leq g_{50} \\ c + dx_i, & if\ x_i < g_{50} \end{cases}$$

Where $x_i$ is the NDVI-value for the ith field parcel, $g_{90}$, $g_{50}$ and $g_{25}$ are $90^{th}$, $50^{th}$ and $25^{th}$ percentiles of the NDVI-distribution for the crop cultivated at the ith field parcel. Parameters a and b are regression coefficients so that the gap is 0 and 0.30 at $g_{90}$ and $g_{50}$, respectively. In the same way, c and d are regression coefficients so that the gap is 0.30 and 0.55 at $g_{50}$ and $g_{25}$, respectively. This means that an NDVI-value higher than the 90th percentile had no NDVI-gap. If an NDVI-value was smaller than the $90^{th}$ percentile the gap increases linearly until the NDVI reached the median ($g_{50}$) where the gap was 0.30. If an NDVI-value was smaller than the median, the gap increased with a slope resulting in a gap of 0.55 and then the NDVI-value reached the lowest quarter. These gap-values were obtained from the official yield statistics of Luke. Compared to the yield level at the $90^{th}$ percentile, the yield loss was 30% and 55% for farms located in the median and lowest quarter of the yield level distribution. The definition of the gap was needed because variation between field parcels was smaller in both low and high NDVI-values rather than values which were close to 0.50. Without this definition, some crops or geographical areas would have had higher gaps than others without any true rationale. Furthermore, the NDVI-values from Landsat were in general smaller than the corresponding values from Sentinel. This could be caused by differences in growing seasons as well as different algorithms used for the satellite images. To avoid possible bias, calculations of the gap based on distribution of the NDVI-values (25th, 50th and 90th percentiles) from the same year, area and crop were carried out. This eliminates all possible bias caused by systematic differences in NDVI-values.

Both the first scoring round and the scoring of the productivity gap (in the second scoring round) were always between 0 and 1. Both scores were then combined. Thereafter, the proximity to waterways was considered and borderline fields (yellow, but close to red) were allocated for extensification.

### 2.3. Soil type and logistic advantages of field parcels used for the 3rd scoring round

In the case of an organic peat soil type, a field parcel with a red light according to the second stage scoring round was determined as dark red in the third scoring round. This means that the land would be directed to afforestation because it failed to hold sufficient value for allocation for extensification as it evidently lacks any future potential for food security. If the field parcel got a yellow light in the second scoring round and its soil type was peat, the parcel was allocated for extensification instead of intensification. On the other hand, especially if the logistic advantages were found to be high for a field parcel with a yellow light from the second scoring round, and the soil type was other than organic peat, the field parcel was allocated for intensification instead of extensification even though it had some disadvantages. In such cases, it was apparent that virtually all the other nearby field parcels were allocated for intensification and hence, discarding one field parcel from a uniform set of intensified parcels was not considered to be rational.

The scoring process was first developed to be moderate with composed boundary values for afforestation and extensification. In order to test the dynamism of the developed tool, we also shifted boundary values to consider a potential situation with more ambitious target setting to be supported by novel policy instruments. Impacts of moderate and ambitious target setting on land allocation depending on farm size, farm type and region were evaluated.

### 2.4. Benchmarking the outcomes of land use optimization tool

The 857 field parcels of the 20 pilot farms were used as validation data for the tool. In addition to this, we benchmarked the outcomes of the land use optimization tool with the farmers' perspectives on the use of the land in pilot farms. Semi-structured interviews were carried out with all 20 pilot farmers at their own farms during spring 2016. The farms were in four areas of Finland and they represented the primary farm types in the area. Interviews lasted around three hours per farm and also other issues besides land use optimization were discussed. Pilot farmers were interviewed without informing the farmers of the outcomes of the land use optimization process. Each farmer had a map of their fields available (either their own fields or that they leased), and they shared their views and experiences on the performance of different field parcels. The views of the farmers were recorded and marked into the field parcel maps for further analysis. Each field was categorized afterwards as: a) evidently the best, however, often meaning most productive fields, but also often having other advantageous characteristics (n = 103), b) underperforming, but with some identified means that might improve their condition (n = 92) and c) poorly performing fields (n = 85). These farmer's scorings were compared to the outcomes of the land use optimization tool after the first and the second round scorings.

We also benchmarked how the outcomes of the land use optimization tool performed depending on the farm size, farm type and region. This benchmarking was carried out both after the first and the third scoring rounds. The distribution of fields in different traffic light categories (in the first round) and land uses (intensification, extensification, afforested) were compared with farm sizes and farm types, and the interaction between them was examined using multinomial logistic regression.

## 3. Results

The developed land use optimization tool was based on a three-step categorization of field parcels according to eight field parcel characteristics (Fig.1). The logic was to first assess the general field parcel characteristics (size, distance from farm center, shape and slope) and to weight each of them according to their importance for a farmer. The impacts of field size and shape on scoring during the first round are shown in Fig. 2. Field size had very strong and systematic impact on the first round scoring. Fields larger than some nine hectares did not, however, get higher scores anymore. If the field was larger than the median size of 1.7 ha, only a low share of fields in the pilot farms was scored as yellow and hardly any as red (extensified). If a small field (< 1.7 ha) was allocated to intensification, it was close to the farm center and also all the other general characteristics were very favorable. Contrary to field size, field shape had only minor contribution to allocation: shape with a very low value of 0.3 ranged quite similarly from green to dark red as a field parcel with a value of 1.0 (Fig. 2).

In the second scoring round, NDVI-based productivity gap was included in assessment. The scoring process was first developed to be moderate (Fig. 3) with composed boundary values for afforestation and extensification. If the productivity gap was higher than 50%, the field parcel was never categorized are green. If the first round score was < 0.55, but the productivity gap was < 30%, the second round scoping shifted the field parcel from yellow to green (Fig. 3). If again the score was 0.30, but the productivity gap was < 30%, the parcel was reallocated from dark red to red pool. Proximity to waterway was considered after assessment of the productivity gap. If a field parcel was next to the waterway and it was categorized as yellow but it was close to the boundary line of red, it was reallocated to the red category instead of yellow (see as orange in Fig. 3). A majority of the field parcels were allocated to sustainable intensification when moderate target setting was used (Table 2). In order to test the dynamism of the developed tool, boundary values were tightened for ambitious target

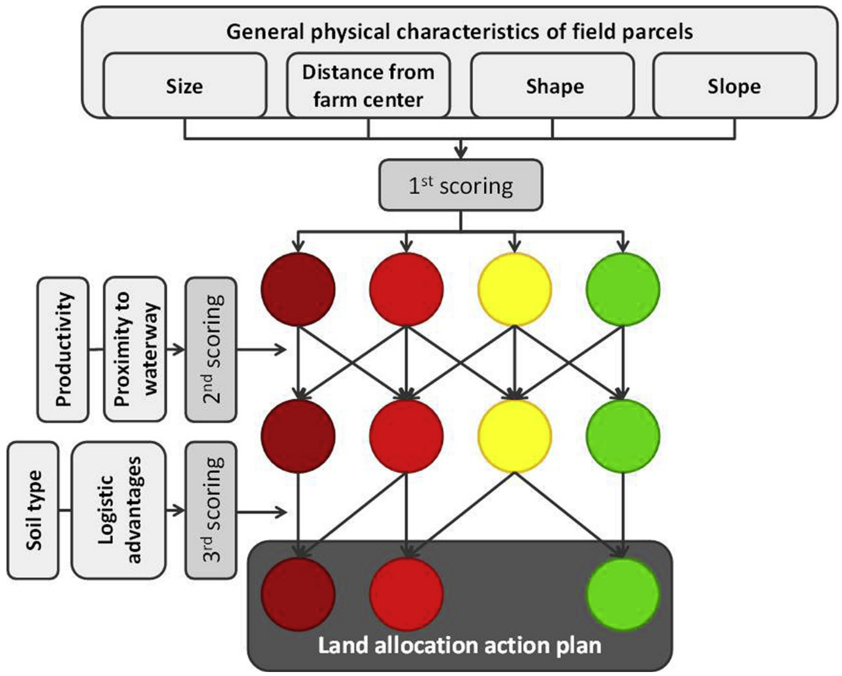


**Fig. 1.** Process chart with traffic lights indicating the three-step scoring system of the land use optimization tool according to which field parcels are allocated to sustainable intensification (green), extensification (red) or afforestation (dark red). The borderline cases after the 1st and the 2nd scoring are shown in yellow.

setting. Thereby, a higher share of field parcels was allocated for extensification and afforestation at the expense of green and yellow field pools (Table 2). If the field parcel was allocated to afforestation during the second scoring round, it remained there also after the third round. Similarly field parcels allocated to sustainable intensification remained as green after the third round. If the parcel was allocated to extensification but its soil type was peat, it was reallocated to afforestation during the final scoring round. Similarly yellow field parcels with peat soil were allocated to extensification. A red parcel was reallocated to the green field pool, if all the other nearby fields were also categorized as green.

The outcome of the first scoring round, that was only based on physical characteristics of the field parcels, indicated that land allocation was strongly dependent on farm size (one-way ANOVA, $P < 0.001$). Less land was directed for the intensified field pool, slightly more was assigned to extensified field pool and again equally to the afforestation pool on small farms (< 30 ha) when compared to very large farms (Table 2). Additionally, a significantly higher share of fields was directed to the yellow pool (Fig. 1) on small farms than on other farm sizes. The impact of the farm size tended to be similar for the first and the third scoring rounds and this was also true for the different farm types. It appeared that the small farms had a lower share of advantageous (green) fields, but a high share of yellow and red fields but not dark red coded fields. The share of field parcels allocated to afforestation (dark red) was actually the highest for the very large farms according to both modest and ambitious target settings for the land use changes (Table 2). Small farms were often specialized in horticulture or horse and sheep production. Hence, farms with low competitiveness and limited prerequisites for conventional production have specialized into niche production. On the other hand, farms with the most favorable fields according to their physical properties were prime crop, pig and poultry producing farms.

It appeared that also the interaction between region × farm size × the farm type was significant ($P < 0.001$). For example, the share of green coded fields declined for small farms compared to large farms in cases where the farm was specialized in dairy production, special crops or horticulture, in contrast to other farm types. When comparing the first and the third scoring rounds in the case of the ambitious target settings for land use changes (Table 2), on very large farms (≥100 ha) virtually all the green coded fields remained in the

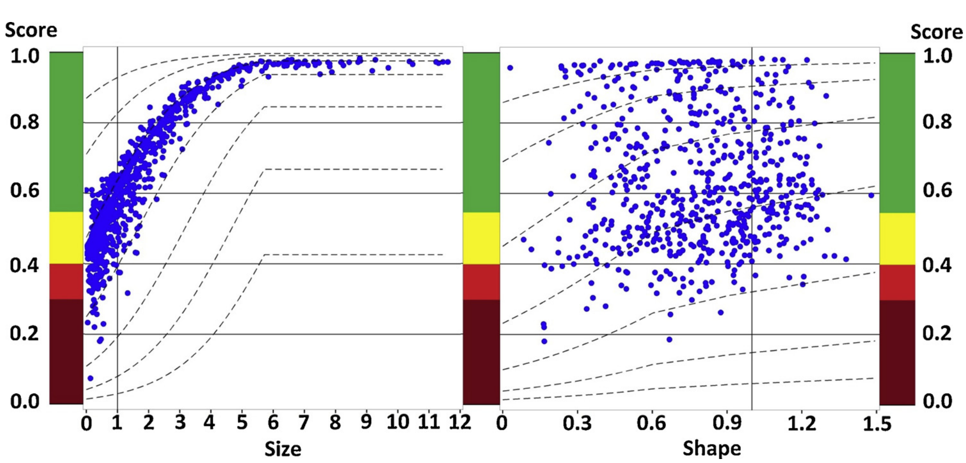


**Fig. 2.** The impact of the size (left hand side) and shape of field parcels (on the right) on scoring in the first round depending on the other parcel characteristics of 857 field parcels of pilot-farms (blue dots). The parcel size has a stronger impact than the field shape. The median is shown with a vertical line (value 1.00 on the horizontal axis, corresponding 1.7 ha for field size) and the traffic lights are as described in Fig. 1. The dashed line represents the score as a function of the size or shape of the field parcel when all other characteristics of the field parcel remain unchanged.

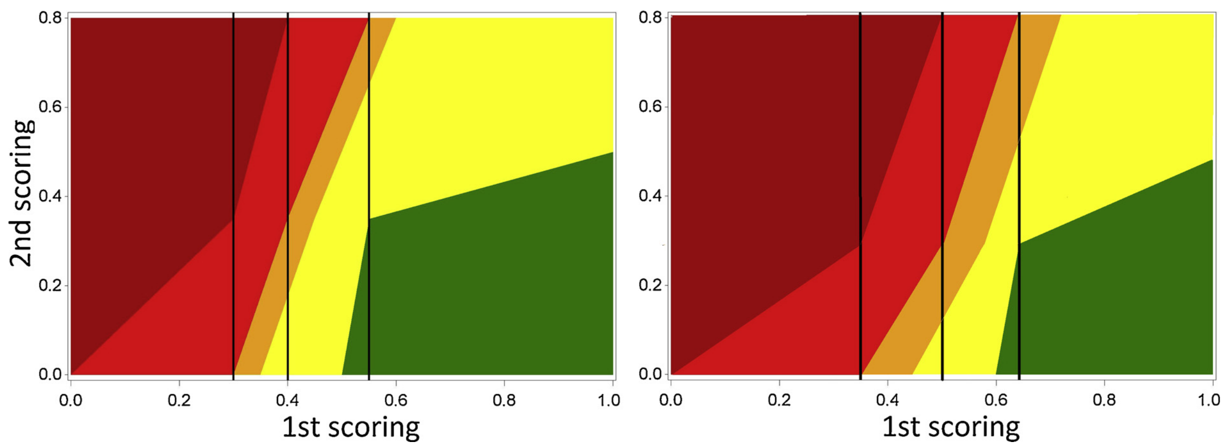


**Fig. 3.** The scoring system used to allocate field parcels depending on their physical characteristics (1st scoring round) and productivity (2nd scoring round with assessment of the productivity gap; where 0 = no productivity gap compared to the best 10% the fields, median = 0.35). On the left side is a case with a modest target setting and on the right side there is another with an ambitious target setting. The black vertical lines indicate the boundary values for the 1st scoring round. The orange colored area indicates fields that were coded yellow, but which are close to the red boundary values and therefore these are turned red if the fields are next to waterways.

pool of sustainably intensified parcels. The share, however, slightly declined for smaller farms. 33%, 26%, 25% and 24% of the fields that had yellow light in the first scoring round turned red (extensified parcels) during the final scoring round for small, medium, large and very large farms, respectively. Correspondingly, 17%, 16%, 15%, 15% of small, medium, large and very large farms, respectively, shifted from red to dark red (afforestation). Furthermore, fields given a yellow light turned red very frequently on horticultural farms (32%), while this was less often for poultry farms (21%), sheep and horse farms (22%) and pig and cattle farms (23%). There was also a tendency for fields given a red light to eventually turn green quite frequently on sheep farms (17%) compared to other farm types (9–14%). Allocation of field parcels to different categories varied depending on region (Fig. 4). A high share of sustainably intensified fields were clustered in southern inland and northern coastal regions, while again a high share of extensified and afforested fields in south-western coastline as well as in inland region and eastern part of the country.

Interviewed pilot farmers tended to rank their fields according to productivity, *i.e.*, at the expense of any other field characteristic. They were able to characterize only 280 of the 857 field parcels. The median for the second round scoring (considering both physical characteristics and the productivity gap of each field parcel) was high (0.77) for the fields that farmers ranked to be the best (Fig. 5). The median was 0.70 for the underperforming fields with identified means to improve conditions and 0.62 for the most poorly performing fields.

## 4. Discussion

Sustainable intensification is a highly current topic for high-latitude agricultural systems, as these areas have struggled with many economic challenges and dissatisfaction of farmers during the last couple of decades, since Finland joined the EU (Niemi and Ahlstedt, 2014). Furthermore, policy measures such as those of the AES are again on the agenda as Finland prepares for the next program reform after 2020. When targeting full scale renovation such as sustainable intensification of agricultural systems (Petersen and Snapp, 2015; Rockström et al., 2017), one of the core challenges is that farmers are no longer aware of the productivity differences between the field parcels. This results from the long-term use of minimized inputs that ignore substantial differences in field characteristics. Highly variable weather, which is typical for high-latitude conditions, further blurs the understanding of the causal relationships for the expression of yields (Peltonen-Sainio et al.,

**Table 2**
Traffic lights indicating the share of land (% of field area) allocated to intensification (green), extensification (red) and afforestation (dark red) as well as the borderline cases between intensification and extensification (yellow) according to the 1st scoring round for general physical characteristics of field parcels and the final 3rd scoring round depending on farm size and farm type when the original modest target settings for land use changes were used (ambitious target settings in parenthesis).

| Farm | The 1st scoring | | | | The final 3rd scoring | | |
|---|---|---|---|---|---|---|---|
| | Green | Yellow | Red | Dark red | Green | Red | Dark red |
| Farm size: | | | | | | | |
| < 30 ha | 54.9 (37.7) | 32.4 (44.2) | 7.6 (16.4) | 0.6 (1.7) | 89.8 (64.4) | 9.7 (32.4) | 0.5 (3.2) |
| 30–59 ha | 66.8 (42.8) | 25.8 (38.4) | 6.8 (17.1) | 0.5 (1.8) | 93.1 (74.3) | 6.4 (23.1) | 0.5 (2.6) |
| 60–99 ha | 71.4 (44.8) | 21.6 (34.8) | 6.5 (18.2) | 0.6 (2.3) | 94.0 (75.6) | 5.4 (21.5) | 0.7 (2.9) |
| ≥100 ha | 76.0 (45.6) | 17.3 (31.2) | 6.1 (19.9) | 0.6 (3.3) | 92.6 (74.4) | 6.5 (21.8) | 1.0 (3.9) |
| Farm type: | | | | | | | |
| Dairy | 64.1 (40.7) | 27.3 (37.7) | 7.9 (18.9) | 0.7 (2.7) | 92.6 (74.7) | 6.5 (22.0) | 0.9 (3.4) |
| Pig | 74.4 (48.2) | 19.5 (33.4) | 5.7 (16.6) | 0.5 (1.9) | 94.4 (78.2) | 5.1 (19.1) | 0.5 (2.7) |
| Poultry | 75.5 (46.6) | 19.0 (36.9) | 5.1 (15.3) | 0.4 (1.3) | 95.4 (79.8) | 4.3 (18.2) | 0.4 (2.1) |
| Horse/Sheep | 61.1 (32.5) | 28.7 (42.0) | 9.1 (21.5) | 1.0 (4.0) | 90.4 (70.8) | 8.3 (24.6) | 1.3 (4.6) |
| Cereal | 72.3 (44.9) | 21.5 (36.0) | 5.7 (16.9) | 0.5 (2.2) | 92.8 (73.5) | 6.5 (23.4) | 0.7 (3.1) |
| Special crops | 72.9 (39.0) | 20.7 (38.3) | 6.0 (20.2) | 0.5 (2.5) | 92.1 (70.8) | 7.2 (25.8) | 0.7 (3.4) |
| Horticulture | 53.0 (26.5) | 33.4 (42.9) | 12.5 (27.6) | 1.1 (3.0) | 89.0 (62.5) | 10.5 (32.5) | 0.6 (5.0) |
| Others | 61.3 (32.8) | 30.0 (43.6) | 7.9 (20.1) | 0.8 (3.5) | 88.8 (64.8) | 9.9 (30.2) | 1.3 (5.0) |

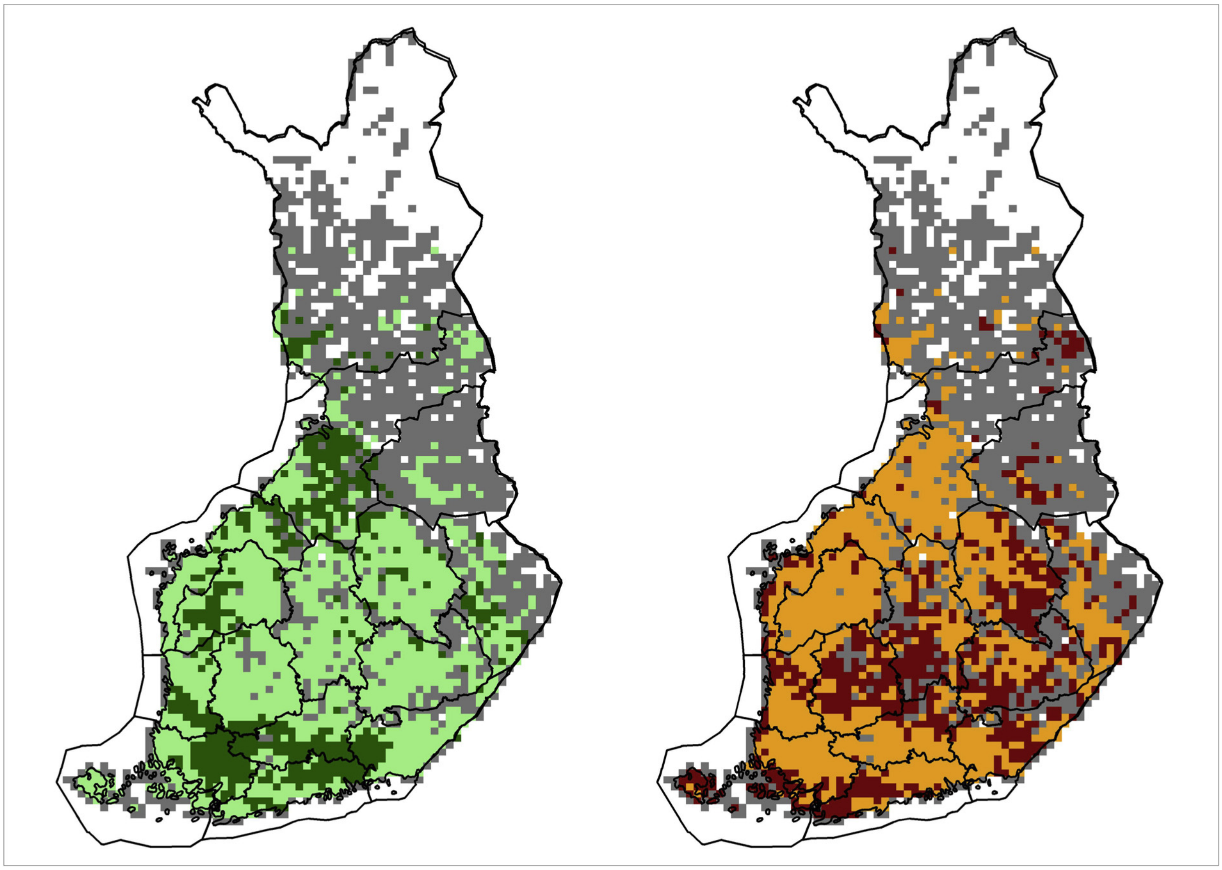

**Fig. 4.** Land allocated by the land use optimization tool to sustainable intensification (left) and extensification or afforestation (right) depending on the region in Finland. Each square in the map equals 10 × 10 square meter land area. Green square indicates that the share of sustainably intensified fields is ≥40%, light green that it is < 40% in the left-hand map, while red color in the right-hand map indicates that the share of extensified and afforested fields is ≥25% and orange that it is < 25%. Gray color indicates that there is less than 100 field parcels in the area and white that there is no fields at all.

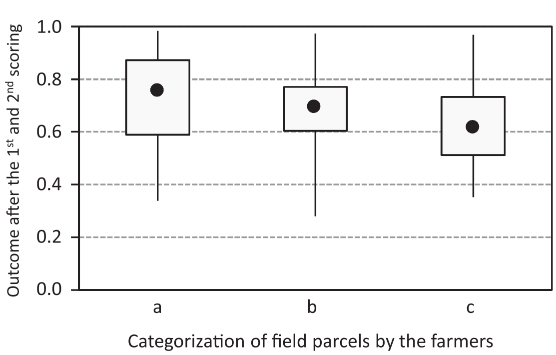


**Fig. 5.** Categorization of the field parcels by the pilot farmers (a = the best, b = underperforming with identified means to improve conditions, and c = poorly performing fields) compared to the outcome of the 1st and the 2nd round scorings of the land use optimization tool. The boxes indicate the lower and upper quartile. The dot within the box is median. Whiskers indicate the most extreme datapoints.

2016b), as does the high share of leased land (Pouta et al., 2012) because a farmer is less familiar with the conditions of leased land. This study confirmed that there were indeed substantial differences between field parcels in their physical characteristics and productivity, even within a farm. This urges not only the development of a tool that facilitates farmers in their decision making but also its immediate implementation. Many field characteristics are important drivers for land allocation, but compromises are also needed (Myyrä and Pietola, 2002; Peltonen-Sainio et al., 2017, 2018). The developed land use optimization tool combines all the necessary information on the field parcel scale, which is currently either lost, hidden or incomparable, to support the farmer's decision making regarding land allocation either for intensification, extensification or afforestation.

### 4.1. Benchmarking scoring with farmers' conceptions

The interviewed farmers were keen on the information provided by the land use optimization tool, especially because the tool revealed productivity differences between field parcels. When the scoring of the land use optimization tool (Fig. 1) was compared to the outcome of field categorizations carried out by the farmers (Fig. 5), it was evident that the farmers faced challenges in their decision making when simultaneously trying to consider and value multiple field characteristics. They often were drawn into comparing fields only according to their yield and even in this case only by identifying the best and the worst parcels. Furthermore, only 280 out of 857 field parcels were ranked by farmers. In fact, this uncertainty or even inability to rank fields was one of the main rationales for the development of the tool which aims to achieve a systematic and comprehensive conception for land allocation across Finland. According to interviews, the pilot farmers often highly ranked fields that tended to be productive consistently without considering other field parcel characteristics, even though a high number of other field characteristics also drive the decision making (Fig. 1) and are also considered to be important for successful farming (Peltonen-Sainio et al., 2018). Nonetheless, the median of the scores provided by the tool was higher for fields that farmers ranked to be the best (Fig. 5). This indicates that farmers were to some extent able to identify their best field parcels, though the scores provided by the tool ranged from poor (0.34) to very high (0.98). Furthermore, the pilot farmers told that they were very interested in gaining additional understanding about the ranking of their fields according to simultaneous consideration of many field parcel characteristics and whether their fields should be intensified or extensified. Extensification *per se* did not cause much offence to the pilot farmers when there were evident rationales for such land use changes. In fact, the pilot farmers were keen on having a more critical land use plan as an outcome of the optimization process, *i.e.*, a higher share of extensified fields parcels, to support the allocation of their near future land renovation efforts. Therefore, we also tested a version with more ambitious target settings to enable the allocation of a higher share of land for extensification. On the other hand, the pilot farmers who participate in research projects do not represent the standard mean of all farmers but most likely belong to the upper quartile, which explains their eagerness for an outcome that challenges them. The farmers again strongly opposed afforestation, as they considered that their ancestors had cleared the forests to create fields in the most favorable regions, often close to the waterways with access to the ecosystem services they provide for farming (Peltonen-Sainio et al., 2015a). Afforestation is an irreversible step that excludes the land from any future production and is thereby considered to impair food security. Despite this, pilot farmers considered that ˜2% of their fields were poor, which is a higher share than the original modest boundary values (Table 2). These poor fields in the pilot farms represent the potential pool for afforestation. Such fields were more typical for small farms and they were located far away from the farm center and waterways. Furthermore, they were small, irregularly shaped and flat, but none of them were on peatlands. Such parcels are often unprofitable (Myyrä and Pietola, 2002) and hence, allocated as green fallow land and nature management fields to provide environmental benefits (Herzon et al., 2011; Ekroos et al., 2013), though their productivity was actually often quite reasonable. These examples indicate that the land use in farms was not irrational or undesirable, as also highlighted by Gao et al. (2010), compared to the outcomes of the tool, which again are likely to facilitate its implementation.

### 4.2. Differences in land allocation depending on farm size, farm type and region

As a high-latitude country, growing conditions in Finland vary considerably depending on region. Therefore, also farm types are partly polarized like dairy and beef production in the northern part of the country, while prime crop production in the South- and West-Finland. The highest total field area is in the coastal regions, but the farms again tend to be large especially in the southern crop production region, where also a majority of the large fields are located. In the southwestern coastline and in some inland regions fields are less uniform in shape than elsewhere, while again in western and northern coastal region they are especially flat.

Land use optimization tool indicated the highest share of sustainably intensified fields for the north-western coastal region and the southern prime crop production region of Finland (Fig. 4). The highest share for extensified and afforested fields were again in inland regions and eastern part of the country. The lowest share of sustainably intensified fields was found for small farms (Table 2). Hence, small farms had the highest share of extensified fields, but they were also often specialized in horticulture or horse and sheep production. Interestingly, farms with low competitiveness and limited prerequisites for conventional production and also for expansion, have adapted by specializing into niche production. This is not necessarily even a feasible option for large or very large farms. It is possible that these special farm types have least opportunities to implement the outcomes of the land use optimization tool due to a low total field area that already challenges farm business. Contrary to these farm types, especially pig and poultry farms, but also southern crop production farms and northern dairy and beef farms had the highest share of sustainably intensified fields. This confirms that the shares of intensified and extensified fields were not attributable to any dominating field parcel characteristic, but depending on region, different parcel characteristics complemented each other.

### 4.3. Implementing, monitoring and impacting policies

The developed land use optimization tool is currently implemented for all 40,000 Finnish farmers via the EconomyDoctor portal (https://portal.mtt.fi/portal/page/portal/economydoctor/) of the Natural Resources Institute of Finland (Luke). The tool will be launched for farmers' use in winter 2019 with strong authentication to safeguard privacy. Farmers may grant access to advisors and neighboring farmers, while other users will have access to compiled materials across regions, farm types *etc*., where a single farmer cannot be identified. This is the means by which this project will share information with stakeholders involved in the landscape planning processes. The tool is routinely updated automatically when new data appears, *e.g.*, changes in the field parcels that have been cultivated (owned or leased) on each farm and regarding the data on NDVI-based productivity gaps. Not only having a distinguished platform for tool implementation, but also applying participation-based methods (Le Gal et al., 2011) with farmers, advisors, researchers and policy makers will pave the way for the tool deployment.

It is important to anticipate – but also after large scale piloting to monitor – the environmental and economic impacts of sustainable intensification and land use changes, as part of this on-going R&D project. Changes on a field parcel scale need to be implemented in a way to provide advantageous landscape structures (Piha et al., 2007; Herzon et al., 2011). An increase in landscape heterogeneity increases the congruence of all studied taxa according to (Ekroos et al., 2013), though the degree of the responses of each taxa in Finland has been attributable to differences in underlying mechanisms. Furthermore, envisaging and monitoring changes in GHG-emissions should be at the core of impact assessments because land use changes are the most powerful means to reduce agricultural GHG-emissions in Finland (Regina et al., 2016). Furthermore, the capacity to reduce nutrient leaching and erosion risks (Puustinen et al., 2010) through land allocation are crucial as one third of the Finnish fields are located next to waterways (Peltonen-Sainio et al., 2015a). The impacts on the farm economy also need to be monitored. The settings of the land use optimization tool can be further fine-tuned if needed to provide the best outcome combining environmental impacts and farm economy. Thereby, sustainable intensification actions may also gain social acceptance from farmers in addition to other citizens who are concerned about the environmental impacts of agriculture and future food security in the context of global change.

One can foresee that the land use optimization tool could provide many opportunities for applications beyond its original target use, supporting sustainable intensification of high-latitude agricultural systems and the allocation of inputs and efforts on the farm. For example, it provides valuable information on the pricing of field parcels considering their sale, purchasing or leasing. Such compiled data and independent scoring of all field parcels according to their characteristics are not currently available to support fair pricing. Hence, those leasing their land aspire for the highest price in the region without sufficiently considering the true value of the field according to its conditions and productivity. Another example is that better, consistent and comparable data on field parcel conditions may support further development and implementation of crop insurance (Pietola et al., 2011), which since 2016 has substituted state crop failure payments in Finland. The land use optimization tool may offer some means of reducing the typical crop insurance risks, such as adverse selection and moral hazard problems (Miranda and Vedenov, 2001) by identifying poorly performing land that should be allocated to greening purposes instead of wasting resources on it.

The land use optimization tool may also support field parcel exchange and arrangements between farms in Finland, which is one of the aims in the recent national strategy (MMM, 2015), and which is also encouraged by the EU Commission with the primary aim to achieve even and sufficiently large farm units and parcel structures to improve the farm logistics and economy (Myyrä and Pietola, 2002). In fact, the goal of field parcel exchange and arrangements is not novel as such. Reinforcing such structural change has aimed uniform farm structure since Finland joined EU, however, without yet being successful. One of the main reasons is uncertainty on the equality of the field parcels exchanged between farms and hence, the suspected risk for disappointment. The developed tool indicates field parcels that are high quality *per se* but far away from the farm center. Such field parcels, when affiliated with another farm, may be closer to the farm center and in better contact with other high-quality field parcels, which again could provide logistic and economic advantages (Myyrä and Pietola, 2002). When assessed by the land use optimization tool, scores for such originally distant field parcels may be elevated due to well-planned field parcel exchange between farms. Hence, the flexible use of the land use optimization tool would provide better opportunities for comparing field parcel characteristics. This may even include systematic numeric scorings for parcel exchange and rationalization between nearby farms, and this would thereby support progress towards more even farm units. It also supports this through encouraging and sustaining field parcel unification plans.

Policy instruments are critical when considering the implementation of the land use optimization tool. The current policy instruments only partly support land allocation for intensified, extensified and afforested purposes (Sorvali and Lehtonen, 2015). Currently, most agricultural subsidies are paid through hectare-based payments which are decoupled from production. Such payments do not require production or productivity *per se*, but only to keep the land in “good agricultural condition”. Hence, the decoupled hectare-based payments may promote “land sharing” more than “land sparing” activities. Restrictions on fertilizer application rates are strict, and due to the Nitrate Directive and current AES rules, may result in more limited fertilizer rates than those needed to attain the higher yields in sustainably intensified fields considering also consistent genetic improvements in yield and nutrient use efficiency provided by plant breeding (Rajala et al., 2017). Contrary to the recent past, support is not currently offered for afforestation of arable land and hence, the hectare-based, decoupled subsidies support more extensification than afforestation. Therefore, it is emphasized that the break-through of such a land use optimization tool developed here, calls for acknowledging its potential in the future development of policy instruments to enable comprehensive changes in the current agricultural subsidy system to result in substantial, targeted land use changes and a combination of environmental benefits with economic sustainability and social acceptability. This has been fostered by a dialogue with the policy makers throughout the development process of the land use optimization tool.

## 5. Conclusions

In this paper we introduced a novel land use optimization and planning tool for the sustainable intensification of high-latitude agricultural systems and for combining environmental and economic sustainability and social acceptance. The developed tool is based on a three-step scoring system based on the physical characteristics and productivity of field parcels. The tool is dynamic as both its boundary values for the allocation of land either to be sustainably intensified, extensified or afforested can be fixed according to changes in social targets and supporting policies. It is also temporally flexible as it can be applied year after year by acknowledging the new information available. It can be applied to all farm types and virtually throughout Finland's > 1 million field parcels. It is thereby, a tool for land use planning and implementation, but also for monitoring changes. Its large-scale implementation beyond piloting, however, calls for further development of policy instruments which are currently more supportive towards land sharing than land sparing activities.

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