

# **Final report for NC-GRASS (01.03.2021 – 30.06.2024)**

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## **1. Goals of the project**

Milk and beef production are the backbone of the Finnish agriculture (6172 farms, 2.26 billion liter of milk, 88 million kg beef production in 2019<sup>2</sup>). Milk and beef farming are interconnected, as 80 per cent of Finnish beef production is coupled to milk production. Male calves of dairy cows are raised for beef production and dairy cows that have ended their production are also slaughtered for beef. This production system is perceived to be a practical approach for reducing the adverse environmental impact. However, milk and beef production are currently being challenged for environmental and social reasons to adopt new production patterns in grass production and livestock feeding to reduce their carbon footprint. In the changing climate with mild winters, rainy springs and autumns, and warmer and longer growing seasons, milk and beef production in Finland will experience unforeseen challenges for both economic and environmental sustainability that may accelerate ongoing structural changes in the coming years. A major risk factor is the uncertainty about the farm-level measures that could be used successfully, cost-effectively and without compromising the continuity of production for reducing GHG emissions and enhancing carbon (C) sequestration into soil<sup>3</sup>. Failure to do so may increase the number of farms that quit milk and beef production, leading to GHG emissions from fields that could otherwise be used mainly for annual crops, an obvious threat to our agriculture and food security. Such alarming situations call for action to maintain and subsequently increase the level of production in the future. Putting our food systems on a sustainable path brings also new opportunities for operators in the food value chain. New technologies and scientific discoveries, combined with increasing public awareness and demand for sustainable food, will benefit all stakeholders. The challenge ahead is huge because it requires integrated knowledge about the complexity of such systems and new transformations needed are only possible by designing and implementing integrated solutions. Therefore, we propose NC-GRASS as a living lab concept with an overarching goal of transforming data and results from past and ongoing research projects into nature-based climate solutions in dairy and beef farming into products and services that will guide the farmers on the road to sustainability and climate neutrality by 2035.

The Government of Finland, in its program on ‘Inclusive and competent Finland – a socially, economically and ecologically sustainable society’, has identified climate change, declining biodiversity and the overconsumption of natural resources among the most critical issues facing humanity. As a part of this broader goal, the research and innovation program (RI program), ‘Nappaa Hiilestä Kiinni’ (Catch the carbon), was designed in 2021 in extensive cooperation with the stakeholders. Different national and international strategies for land use have also influenced the program’s targets. In response to this program call, NC-GRASS was proposed under the ‘Wisdom From Soil’ theme, with the aim to produce research-based information that foresees changes and provides solutions for milk and beef production in Finland to (a) reduce the overall carbon and other GHG emissions from the cattle sector, (b) recommend best management practices (BMPs) for strengthening carbon sinks and reservoirs, (c) strengthen the sustainable use of renewable natural resources and systemic sustainability of milk and beef production, and (d) build a Farm sustainability data network for a nationwide uptake of sustainable milk and beef farming practices.

## **2. Partners and collaborations**

WP1 and WP2 on carbon sequestration in grasslands and their N<sub>2</sub>O dynamics were carried out by University of Eastern Finland (Marja Maljanen) and University of Helsinki (Asko Simojoki) in collaboration with Luke (Narasinha Shurpali). WP3 on digital technologies was led by FGI (Eija

Honkavaara and here team) in collaboration with Luke (Narasinha Shurpali and Panu Korhonen). WP4 on modelling was led by FMI (Liisa Kuulmala) and Luke (Narasinha Shurpali). WP5 was led by Luke (Anniina Lehtilä and Pooja Yadav). WP6 on communication with farmers and other stakeholders was led by Valio (Juha Nausiainen), Yara Suomi (Mervi Seppäläinen), Atria (Sinikka Hassinen). The overall project management (WP7) responsibilities rested with Narasinha Shurpali as a project coordinator from Luke Maaninka. Valio, Yara Suomi, Atria, Snellman, HKScan were the industrial partners who supported the research work in the project, some in kind and some others with financial support. International scientists – Mathew Harrison from Tasmania University Australia, Elizabeth Pattey from Agriculture Canada, Allen Ritz from USDA, USA advised the postdoc researcher Daniel Forster on modelling aspects of the project and participated as coauthors in several papers.

### **3. Project implementation and results**

#### **3.1 Super sites**

##### **Anttila (Super 1)**

Anttila is a grassland cultivated on mineral soil. The soil type varies from Eutric gleysol to Luvic Planosol/Stagnosol (IUSS Working Group WRB, 2007), the topsoil (0-20 cm) being generally silt loam (mean  $\pm$  standard deviation: 25.0  $\pm$  5.6 % clay, 53.0  $\pm$  9.0 % silt, and 22.0  $\pm$  7.8 % sand) based on the USDA textural classification system. The physiochemical characteristics for the topsoil (mean  $\pm$  standard deviation) are: pH (H<sub>2</sub>O) 5.8  $\pm$  0.2, electrical conductivity 14.0  $\pm$  2.4 mS·m<sup>-1</sup>, soil organic matter 5.2  $\pm$  0.9 %, organic carbon 30.0  $\pm$  5.2 g C kg<sup>-1</sup>, total nitrogen 2.0  $\pm$  0.3 g N kg<sup>-1</sup>, C:N ratio 15.0  $\pm$  0.4, particle density 2.7  $\pm$  0.01 g cm<sup>-3</sup>, and bulk density 1.1  $\pm$  0.1 g cm<sup>-3</sup>. The experimental area at the Antilla site, covering 6.3 hectares, was divided into two equal sections. One portion was treated with mineral fertilizer (Nmin), with a dosage of 106:28:50 kg NPK/ha. The full doses of P and K, along with half the dose of N, were applied as a basal dose, while the remaining half dose of N was applied after the first cut. The other portion was treated with biogas digestate slurry (Norg), at a rate of 98:13:83 kg NPK/ha, which was applied after the first cut.

##### **Särkisuo (Super 2)**

Särkisuo is a drained organic site mainly composed of sedge peat. Peat depth at the sites varies from 25 to more than 100 cm. Based on the electrical conductivity and nutrient values, Särkisuo is more nutrient rich and has a better water holding capacity compared to the Pappilansuo site (S3). The Särkisuo site was cultivated with timothy-meadow fescue grass, fertilized on 10 May and the second fertilization event occurred on 25 June. The field was harvested first on 21 June and again on 1 August. Glyphosate was sprayed on the field on 22 September. The field was left to overwinter until next summer when a new rotation cycle was initiated at the beginning of June 2021. The site was ploughed on 7 June, and it was fertilized and sown with wheat and oat mixture and timothy and meadow fescue grass on 9 June. The whole field was harvested on 28 July. That marked the only harvest in the 2021 season since the grass growth was poor.

##### **Pappilansuo (Super 3)**

The Pappilansuo site is a drained organic field rented from a farmer as one of Luke's research sites in 2020 and was reserved as per the landowner's wish as a vegetative buffer zone between the field and an adjacent watercourse. The site was then supporting timothy grass growth along with other natural grass species as weeds. The landowner's plans for this year prevented us from taking up any other management activities except harvesting at this site. The field was harvested with two grass

cuts on 16 July and 2 September in 2020. Spring in 2021 witnessed the regrowth of the existing vegetation and the field was fertilized for the first time on 19 May with the first grass cut followed by the second fertilization on 17 June. The second grass cut was made on 27 July. Following the second cut, the grassland was left to overwinter.

Super sites 1-3 have been collecting all three GHG flux data since 2020. The years 2022 and 2023 are the first years will all GHG fluxes measured at all three research sites in the Maaninka region. Shown below annual GHG balances from 2022 and their relevance to grassland production.

Milk production in Finland relies heavily on grassland management. The growing season is short varying from 105 days in the north to 185 days in the south. The region is characterized by two types of soils: mineral soils and organic soils. Mineral soils are typically well-drained and have a low organic matter content, whereas organic soils are characterized by high organic matter content and high-water retention capacity. Grasslands have the potential to store substantial amounts of carbon in their roots and soil, making them important for soil carbon sequestration. With this in view, we have initiated a long-term GHG monitoring framework for a sustainable grassland management and agriculture at the Natural Resources Institute Finland (Luke) across several agricultural research sites in Finland. The results presented in this study highlight that boreal legume grasslands managed on mineral soils are environmentally sustainable, while those on drained organic soils emit large amounts of GHGs to the atmosphere.

Finland, relies heavily on forage grasslands cultivated both on mineral and drained organic soils (Kivinen, 2005). In the northern part of the country, grassland cultivation occurs mostly on organic soils. Mineral soils vary from being a small sink to a small source of GHGs to the atmosphere. However, drained organic soils, depending upon their hydrology in terms of whether they are well or poorly drained, can be significant sources all three GHGs. The aim of this paper is to compare the performance of grasslands in terms of the characterization of their annual GHG balance and grass yield as affected by the seasonal weather, vegetation (legume grassland vs nonlegume forage grasses), soils (mineral vs organic) and management practices.

The following three grasslands (Figure 1) under investigation are located near the Luke Maaninka research station in Eastern Finland. (A) Anttila is a 6.3 ha site on a mineral soil with a land use history of bioenergy crops and grasslands. Currently, it is a legume grassland with a grass mixture timothy, meadow fescue and red clover. (B) Särkisuo – is a Timothy meadow fescue grassland (6.8 ha) on a drained organic soil with normal and elevated water table levels, and (C) Pappilansuo – is also another grassland (6.9 ha) on a drained organic soil with seminatural vegetation under different tillage options. At each of these sites, CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O flux measurements are being carried out using the eddy covariance (EC) technique (Shurpali *et al.*, 2010). The EC system is standardized at all these sites and consists of a Metek 3D sonic anemometer for turbulent wind components, an IRGA (LiCor 7200 RS) for water vapor and CO<sub>2</sub> and a laser spectrometer (Aerodyne Inc., USA) for water vapor, N<sub>2</sub>O and CH<sub>4</sub> mixing ratios. The 10Hz EC data are stored locally on 16 GB USB disks and on Luke cloud servers. The data are processed, 30 min fluxes are calculated, and missing data gaps are filled as per the standard EC data handling and statistical procedures (Pastarello *et al.*, 2020). After filling the data gaps, the daily, monthly and annual sums of GHG fluxes are computed. Meteorological variables such as air temperature, humidity, shortwave radiation, net radiation balance, PAR, precipitation, atmospheric pressure, soil moisture and temperature, snow depth, soil oxygen content and water table level are monitored as 30 min averages corresponding to 30 min GHG flux values.



Figure 1. Super sites 1-3 (Anttila, Pappilansuo and Särkisuo) in the Maaninka region.

Table 1: Various grassland management activities carried out during 2022 at the three research sites in eastern Finland

Management activity	Anttila	Särkisuo	Pappilansuo
Ditch widening*	---	14 March	---
Date of first fertilization event	23 May	30 May	24 May
Amount of synthetic N applied (N kg ha <sup>-1</sup> )	52	90	84

Date of herbicide treatment	---	8 June	17 June
First grass cut	21 June	30 June	27 June
Summer plowing	---	---	7 July
Second fertilization event	22 June	4 July	8 July
Amount applied (N kg ha <sup>-1</sup> )	44	69	69
Second grass cut	8 September	15 August	---
Ditch widening	---	9 August	---

\*Särkisuo, one of the grassland sites on a drained peat soil needed work on widening the ditch for better drainage of moisture. The ditch preparation at this site was started in the middle of March in 2022 and another drainage work carried out in the middle of August.

With the onset of spring and after snowmelt, all three sites were applied with the first application of fertilizers in late May, the first grass cuts were made in late June. Within a week of the first cut, Anttila and Särkisuo sites were applied with second dose of fertilizers. The Pappilansuo site however, was ploughed in the first week of July, fertilized a day after that for summer establishment of the a new grassland cycle. The second grass cut at the Anttila site was made in early September, in mid-August at the Särkisuo site. The second cut could not be performed at the Pappilansuo site as it was too wet for the harvesting machines to be worked in the field.

From January until early May, all sites emitted low daily amounts of CO<sub>2</sub> to the atmosphere, no winter associated CH<sub>4</sub> and N<sub>2</sub>O emissions were detected. The onset of spring occurred at the three sites on different dates (Table 1). Despite the delayed onset of spring at the mineral site, it started sequestering atmospheric CO<sub>2</sub> much earlier than the organic soils. The daily GHG flux patterns corresponded well with the management operations carried out, prevailing weather conditions and soil characteristics at the respective grassland sites. Considering the net ecosystem CO<sub>2</sub> exchange, the Anttila grassland being a mineral site accumulated the highest amount of CO<sub>2</sub>, the Särkisuo site was a smaller sink, while the Pappilansuo site was a source of CO<sub>2</sub> in 2022. Owing to poor drainage conditions, the organic soils had standing water in the field, thus providing anaerobic conditions conducive for active methanogenesis. The organic grasslands were large sources of methane. The mineral site cultivated with timothy and red clover was efficient in utilizing the applied N fertilizer and was a small source of N<sub>2</sub>O. Owing to poor vegetative growth under wet conditions, the Särkisuo site was a bigger N<sub>2</sub>O source than Anttila. The Pappilansuo site, however, was the largest N<sub>2</sub>O source in 2022 (Table 2). This was because the site did not recover well after the summer ploughing and as a result, the vegetation growth was too poor to utilize the applied N. During the eight weeks following the summer ploughing, the site had high CO<sub>2</sub> losses implying enhanced rate of decomposition and N mineralization.

**Table 2:** Annual individual (CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O) and total GHG balance of grasslands in eastern Finland for the year 2022. All GHGs are expressed as mega gram of CO<sub>2</sub>-equivalents per ha per year. Negative number in the table implies that CO<sub>2</sub> is taken up by the ecosystem, while a positive number indicates that CO<sub>2</sub> is lost to the atmosphere.

Site	Soil type	CO <sub>2</sub>	CH <sub>4</sub>	N <sub>2</sub> O	Total GHG balance
Anttila	Mineral	-9.2	0.1	1.2	-7.9
Särkisuo	Drained peat	-3.5	3.1	5.1	4.7
Pappilansuo	Drained peat	2.6	1.3	9.0	12.9

Our results stemming from continuous monitoring of year-round GHG fluxes are extremely useful in characterizing the grassland biogeochemical processes as affected management practices, soil and vegetation types and prevailing climate. Such data are very useful in calibrating and validating grassland models for predicting grassland responses to future climate. Our results also show that grassland or any other crop cultivation is not a sustainable option on some organic soils such as Pappilansuo with poor drainage. While suggesting that such soils should be discontinued from

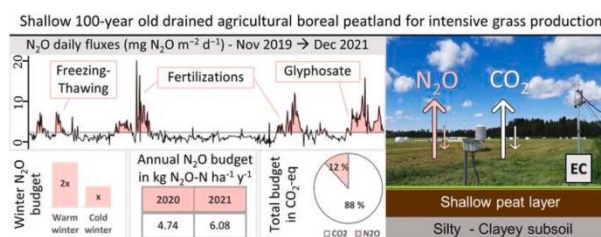
traditional agriculture is easy, asking the farmers to adopt alternative organic soil management options such as wetland restoration and paludiculture is complicated under the present circumstances. There are rural employment and socio-cultural issues that need to be considered. Such soils will continue to be cultivated until the national governments intervene with subsidies and incentive plans for adopting alternative, environmentally friendly options.

### Ruukki NorPeat (Super 4)

The NorPeat field in Ruukki is located in the Pohjois-Pohjanmaa region in Finland and is managed by the Natural Resources Institute Finland (Luke). The ca. 13-ha field is a former minerotrophic peatland, which has been in agricultural use at least since 1933. The peat depth varies through the study field but is generally low, 20-60 cm. The site includes two parcels which are separated by a small road. For research purposes, the fields are divided into 6 plots, four on one and two on another side of the road. The research area has been cultivated with grass-intensive crop rotations, where grass is cultivated for 3-4 years and then sown again after 1-2 years of cereal crops. In 2019, half of the plots were grass and half renewed under barley. In 2020-2021 all of the plots were grass. FMI has collected continuous H<sub>2</sub>O, CO<sub>2</sub> and N<sub>2</sub>O flux measurements with eddy covariance (EC) since 2019 and CH<sub>4</sub> measurements since 2022. The site is introduced in detail by Yli-Halla et al. (2022) and the flux measurement setup is introduced in detail by Gerin et al. (2023). The flux data was processed and gapfilled as in Qvidja (S5). The University of Oulu measures the water balance. Additional chamber measurements were used to test the model in the different plots (personal communication with Maarit Liimatainen/Luke). The different plots were monitored using remote sensing imagery from the European Space Agency (ESA) Sentinel-2 satellites. The leaf area index was estimated using the ESA Sentinel Application Platform (SNAP) Biophysical Processor neural network algorithm as described by Weiss and Baret (2016) and Nevalainen et al. 2022.



Figure 2: Norpeat research site in Ruukki, N<sub>2</sub>O flux data from this site are presented below (<https://doi.org/10.1016/j.agrformet.2023.109630>)



## **Qvidja (Super 5)**

The EC flux measurements were conducted at the Qvidja farm in *Parainen*, Turku Archipelago in southwestern Finland. The soil type is clay loam and the site has been in agricultural use probably for hundreds of years. A detailed site description is available in Heimsch et al. (2021). Shortly, the study field was mainly fertilized and harvested twice during the growing seasons in the study period (2018-2023). In 2021 and 2022, a short period of rotational grazing was conducted: In August 2021, 8 cows were grazing small paddocks within the EC footprint area and were moved to a new paddock every day for 6 days. Similarly, in August 2022, 9 cows were grazing small paddocks for 9 days. The measurements include continuous H<sub>2</sub>O and CO<sub>2</sub> flux measurements with EC method, carbon balance, soil carbon and nutrient stocks together with many controlled experiments at the site. The EC data were gap-filled using a decision tree-based machine learning method called eXtreme Gradient Boosting (XGB) using an ensemble of 10 models. The hyperparameters of each model were determined using grid search and five-fold cross-validation (Vekuri et al. 2023). The models were trained using leaf area index (LAI), air temperature, soil temperature at 30 cm depth, photosynthetically active radiation (PAR), soil water content (SWC), vapor pressure deficit (VPD), and precipitation as environmental drivers. The gap-filled net ecosystem exchange (NEE) was partitioned into gross primary production (GPP) and respiration (TER, also known as Reco) according to the method described in (Heimsch et al. 2021). LAI was obtained as in Ruukki NorPeat.

## **SMEAR-agri Viikki (Super 6)**

The AgriSMEAR Viikki site is a clay field in Viikki, Helsinki and is managed by the University of Helsinki (UH). The field has a rotation of perennial grass with one year of cereal cultivation in between. It has been intensively studied since 2021. The measurements include continuous H<sub>2</sub>O, CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O EC flux measurements, carbon balance, soil carbon and nutrient stocks, and losses of carbon and nutrients with discharge water. NEE was gapfilled as in Qvidja (S5) and LAI was obtained as in Ruukki NorPeat.

## **3.2 WP1 and WP2 (UEF (Marja Maljanen), UH (Asko Simojoki), Luke (Narasinha Shurpali, Hem Raj Bhattarai))**

### **Aims**

The main aim was to collect all published GHG data relevant for northern agricultural soils for a critical review and meta-analysis and identify the effective mitigation options for mineral and organic soils. In addition, GHG measurements at Luke Maaninka (three different experiments) were completed and the annual data from three years (still unpublished) was included in the meta-analysis. The meta-analysis paper is not yet published but will be submitted during 2024. The data still needs to be checked and some statistical tests updated.

### **Methods**

The review showed that there were lot of data available (123 peer-reviewed publications and three unpublished data sets) on annual and seasonal fluxes from boreal and temperate grasslands, annual croplands, and green fallows on mineral and organic soils; 53 peer-reviewed papers on bioenergy studies, as well as studies on pastures and bare soils. A total of 84 parameters relevant for N<sub>2</sub>O, CH<sub>4</sub> and CO<sub>2</sub> fluxes of agricultural soils were collected from each publication when available. A total of 2300+ data lines (sets of parameters) were included in the analysis, whereas 600+ data lines were rejected from the analysis as low quality or irrelevant.

## Results and discussion

Based on our meta-analysis, northern grasslands on mineral soils mineral and grasslands on organic soils were N<sub>2</sub>O sources, and organic soils had higher emissions than mineral soils. Mineral soils were mainly CH<sub>4</sub> sinks, some organic soils were small sources. On average, mineral soils were CO<sub>2</sub> sinks, and organic soils were CO<sub>2</sub> sources, as expected.

To identify the key processes and mechanisms causing the GHG emissions, more detailed information is required not only about the GHG flux rates but also on soil and vegetation properties, land use and cropping history, as well as management practices and environmental conditions on the site. Especially the factors affecting soil GHG production in the hot spots in time and space are unclear. Knowledge about vegetation and soil processes affecting GHG dynamics is important in future studies for giving more insights on how to plan the mitigation methods of GHGs. For this aim the recommended parameters which should be reported together with GHG emission data are shown in Table 3.

<b>Table 3. Soil and climate parameters which should be reported with gas flux results</b> ( <sup>M</sup> = only for mineral soils, <sup>O</sup> = only for organic soils). <sup>A</sup> = topsoil (depth 0–20 cm)		
<b>Required parameters</b>	<b>Method (unit)</b>	<b>Period</b>
Soil type	WRB <sup>A</sup>	-
Soil texture <sup>M</sup>	sand, silt, clay (%) <sup>A</sup>	-
Peat depth <sup>O</sup>	m	-
GWL <sup>O</sup>	m	Growing season mean
Soil pH	pH (H <sub>2</sub> O) <sup>A</sup>	-
Soil C	% <sup>A</sup>	-
Soil N (total, mineral)	% <sup>A</sup>	-
Organic matter content	% <sup>A</sup>	-
Bulk density	g cm <sup>-3</sup> <sup>A</sup>	-
SWC	gravimetric moisture (%) <sup>A</sup>	Growing season mean
WFPS or WHC	vol. moisture <sup>A</sup>	Growing season mean
Crop	Latin name (s)	Growing season
Biomass/harvest	kg ha <sup>-1</sup> yr <sup>-1</sup>	Growing season
Mineral fertilizers	kg ha <sup>-1</sup> yr <sup>-1</sup>	All year
Organic fertilizer (N, C)	kg ha <sup>-1</sup> yr <sup>-1</sup>	All year
Organic fertilizer (type)		All year
Weed/pest control	dose time <sup>-1</sup>	All year
Tillage	method, time, depth (m)	All year
Drainage history	year, depth (m)	Full time
Land use history	year	Full time
Irrigation	dose time <sup>-1</sup>	All year
Annual precipitation	mm yr <sup>-1</sup>	All year
Annual mean temperature	°C	All year
Growing season length	days	Growing season mean
Snow depth	m	All year
Length of snow cover period	days	All year
<b>Recommended parameters</b>		
Soil nutrients (N, P, K, Ca, Mg, S)	mg kg <sup>-1</sup>	-
Basal respiration	g CO <sub>2</sub> m <sup>-2</sup> yr <sup>-1</sup>	All year
Water retention curve		All year

GWL = Ground Water Level, C = Carbon, N = Nitrogen, P = Phosphorus, K = Kalium, Ca = Calcium, Mg = Magnesium, S = Sulfur, SWC = Soil Water Content, WFPS = Water Filled Pore Space, WHC = Water Holding Capacity

### Mitigation methods

Based on the analysis of reviewed data, we could identify some mitigation methods, which seemed to have positive effects on mitigating GHG emissions in both mineral and organic soils, whereas a few methods had positive effects only in either mineral or organic soils, and still others showed negative or unclear effects in both soils as compiled in Table 4.

**Table 4. Some GHG mitigation methods and their effects on mineral and organic soils**

Management	Effect on mineral soils	Effect on organic soils
Continuous vegetation cover	+	+
Use of nitrification inhibitors	+	+
Grass instead of annual crops	+	+
Bioenergy cultivation	+	+
Selection of crop species	+	+
Optimizing N fertilization	+	+
Fertilizer type (e.g. urea instead of ammonium nitrate)	+	+
Soil pH specific management	+	+
Cultivation of N <sub>2</sub> -fixing plants	?	+
Use of lower tillage intensity	?	?
Avoiding tillage	?	?
Timing of management practices	?	?
Growing grass for silage	?	?
Grazing	-	-
Sand addition	?	-
Increasing ground water level	n.a.	+
Restoring drained soils towards natural stage	n.a.	+
Afforestation	?	?

### 3.3 Luke contribution to WP1 and WP2.

The aims, hypotheses, results and conclusions from the Research Council of Finland funded research project ENSINK to PI Narasinha Shurpali are of significance to the MMM funded NC-GRASS project. ENSINK aims to understand N<sub>2</sub>O flux dynamics in a legume-based grassland under boreal climate. Ecosystem of interest in ENSINK is a grassland cultivated with red clover and timothy on a mineral soil in Maaninka region. In this project, we aim to seek answers for the following questions:

1. Does legume-based grassland lower the emissions of N<sub>2</sub>O from boreal mineral soil?
2. Can legume-based grassland act as a sink of atmospheric N<sub>2</sub>O?
3. What is the role of red clover as legume in N<sub>2</sub>O flux in the legume-based cropping system?  
Does it promote reduction of soil N<sub>2</sub>O?
4. What biotic and abiotic variables in soil take part in regulating N<sub>2</sub>O flux?
5. What is the role of root-system, soil, and their interactions in N<sub>2</sub>O flux?

Currently, all the data from the proposed ENSINK experiments are collected and being processed. The task includes processing the isotope data of  $^{15}\text{N}_2\text{O}$  and  $^{15}\text{N}_2$  and calculating the gross rates of  $\text{N}_2\text{O}$  and  $\text{N}_2$  consumption and production,  $\text{N}_2\text{O}$  flux rates, characterizing the soil physical and chemical properties and quantification of nitrous oxide reductase, nosZ genes. These data were obtained by conducting a 3-month intensive experiment under controlled condition in laboratory (mesocosm study) and by conducting five field campaigns in growing season of 2022 in field conditions. We have used state-of-the-art stable isotope and molecular biology techniques for these studies. We have used  $^{15}\text{N}_2\text{O}$  isotope pool dilution technique to quantify the gross emission and uptake of  $\text{N}_2\text{O}$  from both laboratory and in-situ conditions. We have measured the  $\text{N}_2\text{O}$  fluxes on a weekly basis for over 2 months period from laboratory experiments and on a bi-weekly basis from the field during the summer of 2022. Additionally, in our in-situ study we have measured the soil profile  $\text{N}_2\text{O}$  concentration at the same interval as the gas flux measurement. These data are very crucial for understating the effect of root growth in  $\text{N}_2\text{O}$  production and consumption. Soil samples collected from both, mesocosm and field study were recently processed for nosZ I and II quantification in SLU Sweden under the supervision nosZ experts, prof. Sara Hallin and Dr.Christopher Jones.

### **3.3 WP3 – FGI and Luke**

Objective of WP 3 was to develop, assess and apply novel remote sensing and artificial intelligence (AI) based technologies for grass growth parameter retrieval that are needed in precision farming and estimation of GHG emissions and in process-based models. Different UAS based remote sensing techniques were evaluated. Secondly, the potential of using open Sentinel datasets in crop parameter estimation were evaluated.

During the project it was seen that a satellite-based approach could be potential to assess the cultivation intensity and quantify the greenhouse gas (GHG) emission potential associated with drained organic soils in Finnish silage grass production systems. Organic soils, prevalent in Northern European agricultural landscapes, play a crucial role in carbon sequestration and storage. However, the cultivation practices employed in these areas may inadvertently release substantial amounts of GHGs, contributing to climate change. Utilizing remote sensing data, could be possible to evaluate cultivation intensity of organic (Dystric and Sapric Histosols) field parcels used for grass production by assessing number of annual harvest events as observed from changes in vegetation indices in Finnish grass production regions. The frequency of harvest events is linked to the presence of excess water, hindering efficient production on the parcels and concurrently influencing GHG emission patterns emanating from the fields.

#### **3.4.1 Materials and methods**

FGI and Luke provide high quality multi- and hyperspectral drone remote sensing equipment and analytic tools for the study. Yara has developed tools such as Atfarm and Yara N-Sensor to improve the N-Use Efficiency in farmer fields, which use satellite images (with a pixel resolution of about 10-20 m) and serve as a precision cultivation tool that allows real-time adjustment of fertilizer volume during fertilization. These tools currently address precise N requirements in different parts of a farmer's field. However, they are not yet calibrated to fertilizer rates and associated with actual  $\text{N}_2\text{O}$  emissions.

### 3.4.2 Datasets for crop parameter estimation using remote sensing

New remote sensing datasets and corresponding field references were acquired for Tasks T3.1, T3.2 and T3.3 using drones and satellites.

**Test areas:** Test areas with different sizes were used ranging from scientific trials to production farms and the entire Northern Savonia region.

- The Luke's Maaninka test area was the major research area. The areas included the Rantapelto trials (25.9 ha), particularly the nitrogen trial, as well as the supersites Pappilansuo (17.2 ha), Särkisuo (17 ha), and Anttila (11.2 ha) (Figure 1). In these areas RGB, multispectral and hyperspectral drone datasets and satellite image datasets were used. Luke was taking reference measurements in these sites. Data capture in Maaninka Rantapelto which consist of plot trials was done in co-operation with "Remote sensing methods to support feed production REHUDROONI" (North Savo ELY Centre) project.
- In Southern Ostrobothnia, 19 drone datasets from 8 different farms were collected in 2022 from the 1st (6-7.6) and 2nd (18-19.7) harvests (Figure 2). Datasets included RGB and multispectral drone images and Sentinel-2 satellite images. Valio took four sample points in each parcel to provide references about the biomass and D-value. Furthermore, two farms from the first cut were with Yara's fertilization experiment (two square areas: without and with fertilizer). Data collection was jointly with the Interreg Botnia-Atlantica CyberGrass I project.
- Grass parcels in the Northern Savonia were monitored during 2021 (1.4-30.9.2021) and 2022 (1.5-30.9.2022) to study cultivation activity and draw conclusions about the relationship between water management, productivity, and carbon emissions (Figure 3).

**Drone data:** Drone data capture was done using a DJI Matrice 300 RTK (M300) and a DJI Matrice 600 (M600). The M600 was employed to capture hyperspectral imagery with two Specim AFX pushbroom hyperspectral cameras, flown in separate flights. The Specim AFX hyperspectral cameras integrate a computer and a high-end GNSS/IMU unit. The AFX10 VNIR camera (2.1 kg, 400–1000 nm, spectral binning of 2) had a spectral resolution of 5.5 nm, a spectral sampling of 2.68 nm, 224 bands, 1024 spatial pixels, and a focal length 15 mm. The AFX17 SWIR camera (2.4 kg, 900–1700 nm, no spectral binning) had a spectral resolution of 8 nm, a spectral sampling of 3.5 nm, 224 bands, 640 spatial pixels, and a focal length of 18 mm. The M300 was mounted with a Zenmuse P1 RGB camera of a 45-megapixel full-frame sensor with interchangeable fixed-focus lenses on a 3-axis stabilised gimbal, a 4.4 µm pixel size with a DJI DL 35 mm f/2.8 lens and RTK GNSS, and a Micasense Altum multispectral (MS) camera, composed by five VNIR bands. More details of the flight and camera settings can be found from Oliveira et al. (2024) and Pitkänen (2023).

The RGB and MS imagery were processed with Agisoft Metashape software, which is a professional tool for photogrammetric image processing. Outputs were reflectance calibrated orthomosaics and point clouds. The Specim AFX10 and AFX17 datasets were processed using the Specim CaliGeoPRO v2.3.12 software. More details can be found in Oliveira et al. (2024) and Pitkänen (2023). Overview of the drone data collection in Maaninka in 2021-2022 is shown in Table 5 and Figure 1.

The physical reference data from experimental trial located in Maaninka "Rantapelto" was used to train machine learning models. The field data for training consisted of 60 samples of fresh yield (FY), dry matter yield (DMY), digestible organic matter in dry matter (D-value), neutral detergent

fibre (NDF), water-soluble carbohydrates (WSC), and nitrogen concentration (N<sub>cont</sub>). It was established in 2018 by the Natural Resources Institute Finland (Luke) in Maaninka, Finland (Central Finland, 63° 8' 43.22" N, 27° 18' 46.20" E, loam soil). The experiment tested the effects of mineral and organic N fertilisation on grass yield production with a split plot design including four replicates, three main plots (fertilisation type: no cow slurry, cow slurry applied once, and cow slurry applied twice during the growing season) and five subplots (total nitrogen 0, 150, 250, 350, or 450 kg N ha<sup>-1</sup> year<sup>-1</sup>). The plot dimensions were 1.5 × 8 m, and each plot was separated by a similarly sized cover plot. The plant material was pure timothy (*Phleum pratense* L. cultivar 'Nuutti') cultivated as typically for silage grass. The agronomic details of the experimental setup are described in more detail in Termonen et al. (2022) and Oliveira et al. (2024).

The parcels for the production parcel estimation were selected in cooperation with project pilot farmers, Valio Artturi® Korjuu- ja palvelu, and the researchers (Figure 2). Four grass samples were taken from each grass field parcel to provide FY values. One sample covered a 0.5 m by 0.5 m surface area, and each sample was located 30 meters from the adjacent sample. The samples were cut from a 10 cm cut height. The FY values of the in-situ measurements were weighed at the site using a scale and were then transformed to represent 1 m<sup>2</sup> FY sample weights. The geolocations of the center points of each in-situ measurement were measured with a GNSS receiver for further analysis. In total, 40 in-situ measurements were collected from the first cut and 32 from the second cut. The analysis was done on the same day as the UAS data collection. More details about the dataset are given by Pitkänen (2024).

**Table 5.** Overview of the drone data collection in Maaninka 2021-2022.

Area	2021				2022		
	19-20.5.	9-11.6.	19-20.7.	27.8.	15.6.	20-27.7.	30.8.
Pappilansuo (SUPER 3)	RGB, MS, SWIR	RGB, MS	RGB, MS	RGB, MS		RGB, MS	RGB, MS
Anttila (SUPER 1)	RGB, MS	MS, SWIR	MS, VNIR, SWIR	RGB, MS, SWIR	RGB, MS	RGB, MS	RGB, MS
Särkisuo (SUPER 2)			RGB, MS	RGB, MS, SWIR			RGB, MS
Rantapelto	RGB, MS, SWIR	RGB, MS, SWIR	RGB, MS, VNIR, SWIR	RGB, MS, VNIR, SWIR	RGB, MS, VNIR	RGB, MS, VNIR, LiDAR	RGB, MS, VNIR, LiDAR



a)



b)



c)



d)

Figure 3. Drone datasets a) Rantapelto (25.9 ha), b) Pappilansuo (17.2 ha), c) Särkisuo (17 ha), and d) Anttila (11.2 ha).

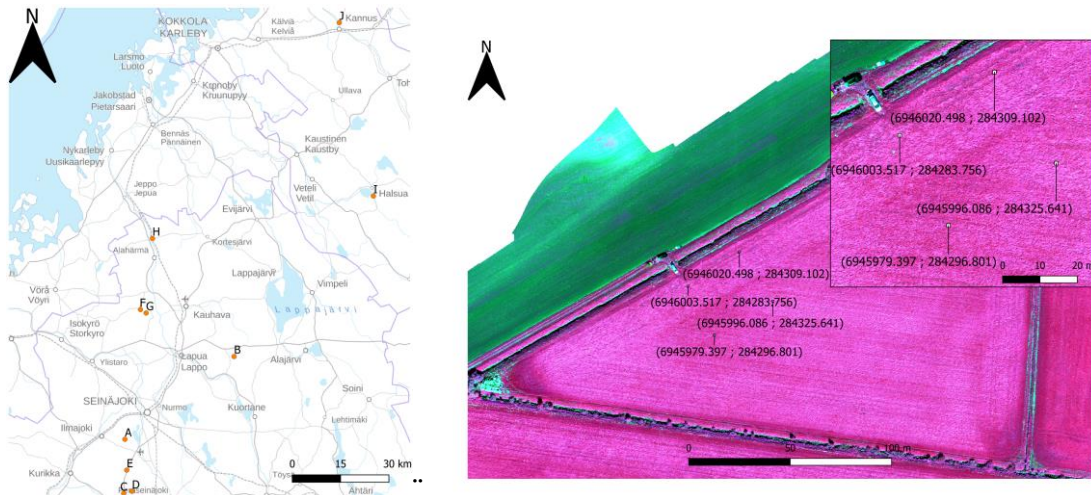


Figure 4 Farms selected for the real farm experiments in South Ostrobothnia (left) and an example of the in-situ measurement locations (right)

### Satellite data for analysis of fresh yield in Southern Ostrobothnia:

The selected S2A atmospherically corrected image products were downloaded from the European Space Agency’s (ESA) Copernicus Open Access hub ESA’s SNAP tool was used for the cropping and resampling pre-processing tasks. The pre-processed satellite images were exported in GeoTiff format. The UAS FY model results were used as reference data for S2 data based FY estimations. The time gap between in-situ sampling and S2 overpasses was chosen to be  $\pm 3$  days or less. Cloud and cloud shadow-free image data was scarce, and Sentinel-2 images were found for only four out of 18 parcels.

**Satellite data for analysis of cultivation activity in Northern Savonia.** Sentinel-2 L2A data was used in this project to extract time series of several vegetation moisture related remote sensing indices for each growth parcel. The annual parcel information containing crop species is openly distributed by The Finnish Food Authority (Ruokavirasto, 2023). Both years, only parcels reported to grow grass (crop codes 6121 and 6210 in the data) in the area of interest were included in the processing. The total number for parcels in the area of interest – covering five regions in the central Finland – was approximately 170 000 and had a total area of about 3 675 km<sup>2</sup> (Figure 4).

The index extraction was done with EODIE toolkit (Wittke et al. 2023) in Puhti high-performance computing environment of the Finnish IT Center for Science. The extracted indices are listed in Table 6. Additionally, OPTRAM index (Burdun et al. 2020) was calculated as a postprocessing step.

The length of the time series varied between years. For 2021, the time series started at 1<sup>st</sup> of April and continued to the end of September. For 2022, the time series started from early May and continued to the end of September.

### Other datasets

Catch the Carbon project “Maaperätiedon kehittäminen (MaaTi)” provided organic soil database over Finland and it was utilized in this project to find grass parcels that are located in organic soils. A farmer who is growing grass in multiple locations provided information about his harvest dates. This was utilized when testing methods to find harvesting/cutting times.

For the large scale analysis the study area were selected to cover areas in middle of the Finland (Pohjois-Savo, Keski-Suomi, Pohjanmaan maakunnat: Figure 5). In the area had altogether 722 883 ha of grass parcels which is 39% of the total area of the agricultural parcels (situation in year 2021). Furthermore, 142 236 ha of those grass parcels were located in organic soils in which is 9% of the total area of the parcels in the area.

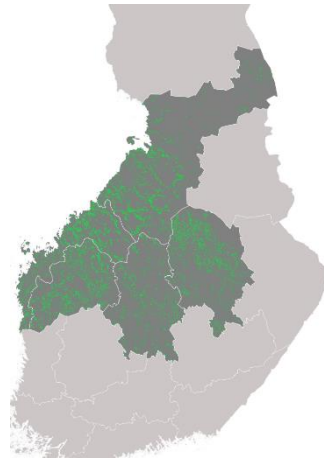


Figure 5. An overview of the grass parcels processed in the project shown in green, on top of area of interest with dark grey.

Table 6. Remote sensing indices calculated from Sentinel-2 L2A data. Sentinel-2 bands are referred to with their numbers.

Index abbreviation	Index name	Index formula	Reference
NDVI	Normalized difference vegetation index	$(B04 - B08) / (B04 + B08)$	Rouse et al. (1973)
NDMI	Normalized difference moisture index	$(B08 - B11) / (B08 + B11)$	Gao (1996)
NDWI	Normalized difference water index	$(B03 - B08) / (B03 + B08)$	McFeeters (1996)
TCTw	Tasseled-Cap transformation wetness	$B02 * 0.2578 + B03 * 0.2305 + B04 * 0.0883 + B08 * 0.1071 - B11 * 0.7611 - B12 * 0.5308$	Kauth & Thomas (1976); multipliers for Sentinel-2 Shi & Xu (2019)

### Machine learning for grass quality, quantity estimation and sensor comparison

The machine learning process included feature extraction, feature selection and supervised learning process. Polygons were manually created in QGIS to match the location of the grass experimental plots (8 m x 1 m) and used to extract several features from each camera reflectance orthomosaic and from the CHM. In total, there were 17578 features for AFX10, 15225 features for AFX17, 50 features for Altum, and 30 features for RGB camera. As the number of extracted features was much higher than the number of reference samples, feature selection techniques were applied to identify the most relevant predictors for each grass parameter. The selected features were used to create RF prediction models for the parameters analysed in this study. The accuracy of the models was



Figure 3. The method was tested against in-situ data of cut times from a collaborating farmer. After a cut, the NDVI values rapidly drop due to loss of vegetation. Among growing season, the vegetation starts recovering, resulting to higher NDVI values. However, at the end of the growing season where final cuts can happen, vegetation recovery might not occur, challenging the detection of the cutting time. Thus, the analysis was focused on the period between 15<sup>th</sup> of May – 15<sup>th</sup> of September. Parcels with less than 7 satellite observations were excluded from the analysis due to temporal gaps in the data. For OPTRAM index calculation, dry and wet edge were determined through a visual analysis from test site. The edges seemed to work also when scaled to larger areas, when tested with NDVI/STR scatterplots from three Sentinel-2 tiles from different parts of the area of interest. Thus, the edges were used both years in calculating OPTRAM values for all crop fields.

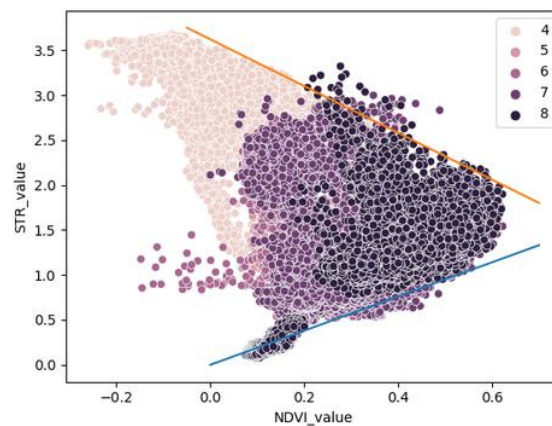


Figure 7: Definition of dry (blue line) and wet edge (orange line) for OPTRAM index. Plot includes datapoints from April (4) to August (8).

## Machine learning for grass quality and quantity estimation

The results indicated accurate estimation results; the best normalised root-mean-square errors (NRMSE) were 8.4% for the quantity parameters, and the best NRMSEs for the quality parameters were 7.44% for Ncont, 1% for D-value, 1.24% for NDF, and 12.02% for WSC. The hyperspectral datasets provided the best results, whereas the worst accuracies were obtained using the crop height model and RGB data. The integration of the VNIR and SWIR hyperspectral cameras generally provided the highest accuracies. Different models were compared using Scott-Knott test (Table 7). Assessment showed that the HS-VNIR\_HS-SWIR combination was among the best group results for all quality and biomass parameter estimations. Similarly, MS-VNIR\_HS-SWIR was in the group of best models for all parameters, except for Ncont. The multispectral camera feature set alone (MS-VNIR) was among the best models for WSC and NDF. Considering estimations with single sensors, the best models were obtained with the HS-SWIR for DMY, D-value and NDF, with the HS-VNIR for Ncont, D-value and WSC, and with MS-VNIR for NDF and WSC. Full results are provided by Oliveira et al. (2024). The trained machine learning models from the Maaninka research station (Rantapelto) were further used at the Anttila supersite to estimate biomass. Results indicated realistic performance with significant variation of yield in the field (Figure 7).

**Table 7:** Best models according to the Non-Parametric ScottKnott ESD test for dry matter yield (DMY), fresh yield (FY), nitrogen concentration (Ncont), digestible organic matter in dry matter (D-value), neutral detergent fibre (NDF), and water-soluble carbohydrates (WSC).

	Estimation model
DMY	HS-SWIR, MS-VNIR HS-SWIR, HS-VNIR HS-SWIR
FY	HS-VNIR HS-SWIR, MS-VNIR HS-SWIR
Ncont	HS-VNIR, HS-VNIR HS-SWIR
D-value	MS-VNIR HS-SWIR, HS-VNIR HS-SWIR, HS-VNIR, HS-SWIR
NDF	MS-VNIR HS-SWIR, HS-SWIR, HS-VNIR HS-SWIR, MS-VNIR
WSC	MS-VNIR, HS-VNIR, MS-VNIR HS-SWIR, HS-VNIR HS-SWIR

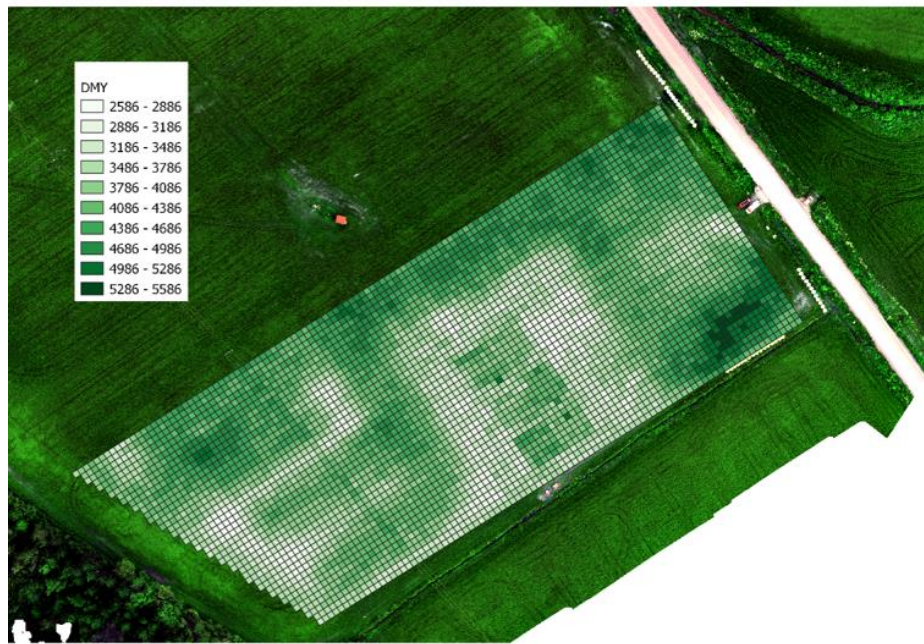


Figure 8. Biomass map of Anttila supersite.

#### Fresh yield estimations for production parcels

The results of FY estimations with parcel specific linear models for the first cut data are shown in Table 8. The best UAS model for FY estimation was for a parcel I first cut, with a NRMSE of 7.1 % and  $R^2$  of 0.943. On the other hand, the best NRMSE for all UAS datasets was for parcel F first cut data with NRMSE of 3.3 %, however, the parcel F had  $R^2$  of 0.463. The best  $R^2$  value (0.984) was obtained for the first cut parcel H dataset. Overall, UAS datasets from both cuts yielded 18.2 % NRMSE and 0.65  $R^2$  on average. The performance assessment results of the Sentinel-2 based FY models, when trained using the FY from the UAS estimated yield map, are shown in Table 8. The NRMSEs were under 13% in all of the parcels, and the  $R^2$  values were over 0.6 in the first cut datasets. However, the low  $R^2$  value of the second cut dataset for parcel H indicated the worst fit of the four S2 models. The first cut models produced reasonably accurate estimations of the FY values based on the UAS model predictions. The worse  $R^2$  value for parcel H could be caused by varying illumination conditions in the UAS data. It could be concluded that the Sentinel-2 data-based yield estimations showed good potential with an NRMSE of 9.5% and an average  $R^2$  of 0.65 for all datasets.

Table 8: First cut date, area, mean fresh yield (FY) field measurement, estimated FY from the UAS linear model, NRMSE and  $R^2$  from LOOCV-method

Date	Parcel	Reference mean from FY samples (kg/ha)	Estimated FY from UAS model (kg/ha)	NRMSE (%)	R2
6.6.2022	A	19650	19680	9.5	0.628
7.6.2022	B	19220	19570	43.5	0.231
6.6.2022	C	24970	26900	3.9	0.406
6.6.2022	D	21620	22170	15.9	0.34
6.6.2022	E	9440	39402	16	0.0004
7.6.2022	F	15670	14910	3.3	0.463
7.6.2022	G	21400	24780	13.8	0.788
10.6.2022	H	25200	22790	39.6	0.984
10.6.2022	I	19400	16950	7.1	0.943
10.6.2022	J	11000	13940	24.1	0.754

Table 9. Sentinel-2 (S2) Random Forest (RF) model performance estimation statistics: Date, Area, NRMSE, R2, Fresh Yield (FY) difference between S2 results and farmer measurements, FY difference between S2 results and in-situ FY measurements,

Date	Parcel	Cut	NRMSE (%)	R2	Difference between S2 results and farmers measurements (%)	Difference between S2 results and in-situ measurements (%)
6.6.2022	B	1st	9.835	0.633	27.6	9.4
10.6.2022	I	1st	12.391	0.759	13.1	6.1
10.6.2022	J	1st	12.889	0.788	33.1	6.2
19.7.2022	H	2nd	2.796	0.402	11.8	1.1

## Satellite image time-series analysis of activities in production fields

Supersites were observed from Sentinel-2 satellite time series for biomass estimation and to monitor human-induced activities in the fields. Analysis of the Anttila supersite showed that cuts were clearly visible in the time series (Figure 9). Supersite was divided to 4 sub-areas for further analysis (Figure 10). This analysis showed that the Area 4 was growing faster than other subareas in the beginning of the growing season. In 2022, area 1 reached the same level of growth than area 4 at 20<sup>th</sup> of May and areas 2 and 3 5<sup>th</sup> of June. In 2023, areas 1, 2 and 3 reached the growth of area 4 at 20<sup>th</sup> to 25<sup>th</sup> of May.

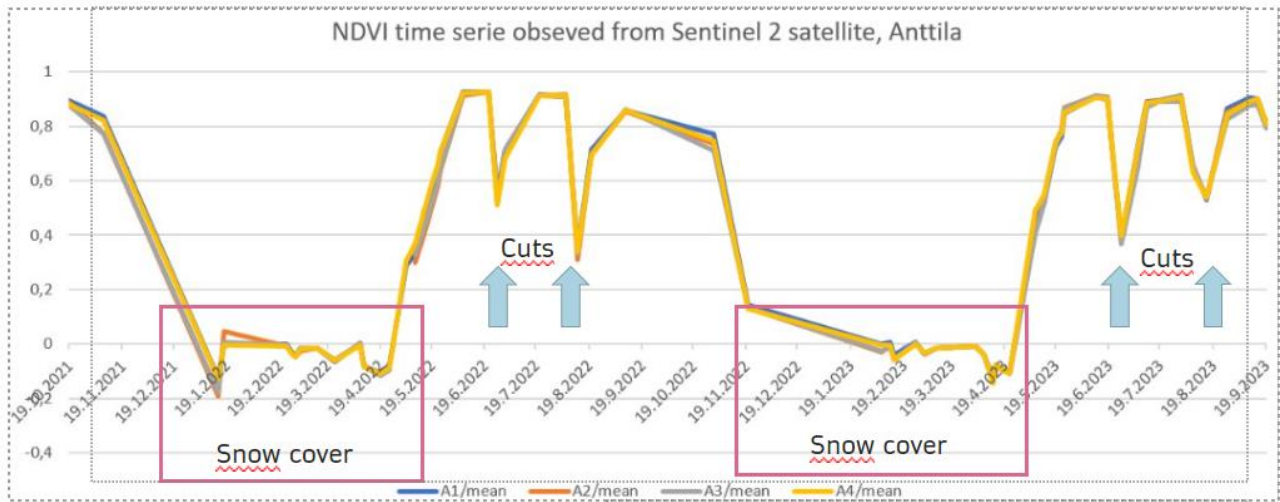


Figure 9. NDVI time serie observed from Sentiel-2 satellite.



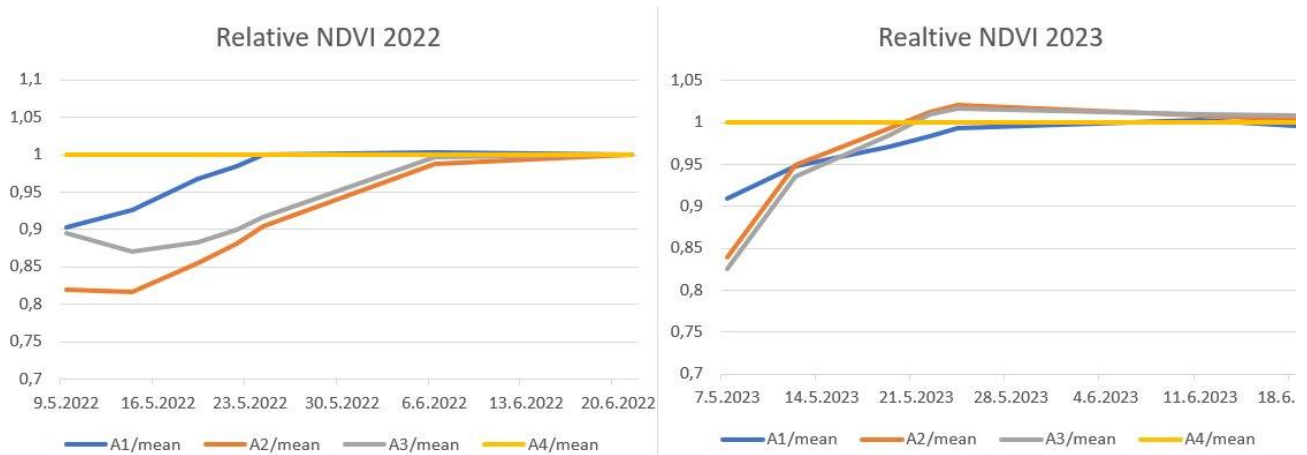


Figure 10. Monitoring of multitemporal Sentinel-2 NDVIs in Anttila supersite.

Automated detection of how many times grass parcels were harvested was tested against using data from farmer about harvesting times. The negative values of first derivative shows the time periods when biomass in the field is decreasing.

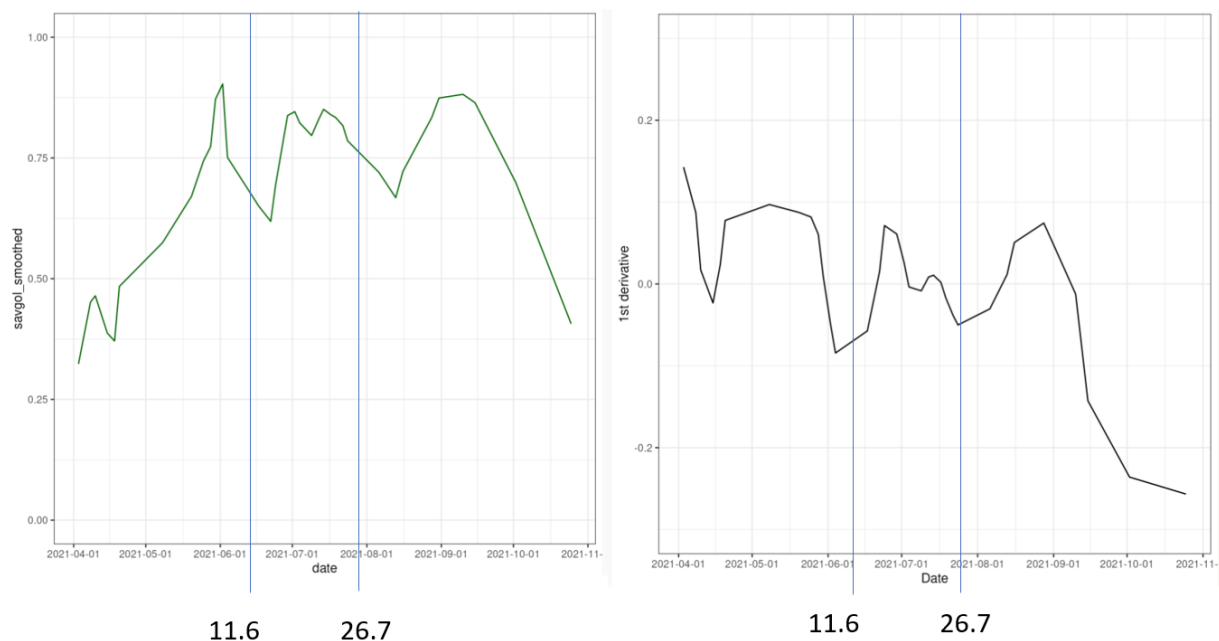


Figure 11. Left: An example of smoothed NDVI time serie from parcel which was harvested 11<sup>th</sup> of June and 26<sup>th</sup> of July. Right: First derivative of the time serie. Negative 1<sup>st</sup> derivatives indicate the cutting periods.

### Machine learning for CH<sub>4</sub> emission estimation (T3.4 – Luke - Shurpali)

As a part of this task, we have used the novel machine learning tools to assess wetland methane emissions, as they have a significant impact on the global climate system. However, the current estimation of wetland CH<sub>4</sub> emissions at the global scale still has large uncertainties. This work has been done in collaboration with scientists from the Purdue University in the USA. In this research, we developed a multi-model ensemble (MME) estimate of the emissions using six distinct machine-learning approaches and in situ CH<sub>4</sub> fluxes from both chamber measurements and the Fluxnet CH<sub>4</sub>

network to reduce uncertainties. Precipitation, air temperature, soil properties, wetland type, and climate type were considered in developing six models. The MME of these six models was then extrapolated to the global scale to estimate CH<sub>4</sub> emissions from 1979 to 2099 (Figure 12). We found that the annual wetland CH<sub>4</sub> emissions will increase significantly by the last two decades of the 21st century. Northern Europe and near-equatorial areas are the hotspots of wetland methane emissions. Global CH<sub>4</sub> has high emissions in the summer while low emissions in the winter. The spatial and temporal variations can be mainly explained by air temperature and precipitation. The uncertainties mainly come from in situ data with uneven spatial distribution and unchanged assumptions of the wetland area data.

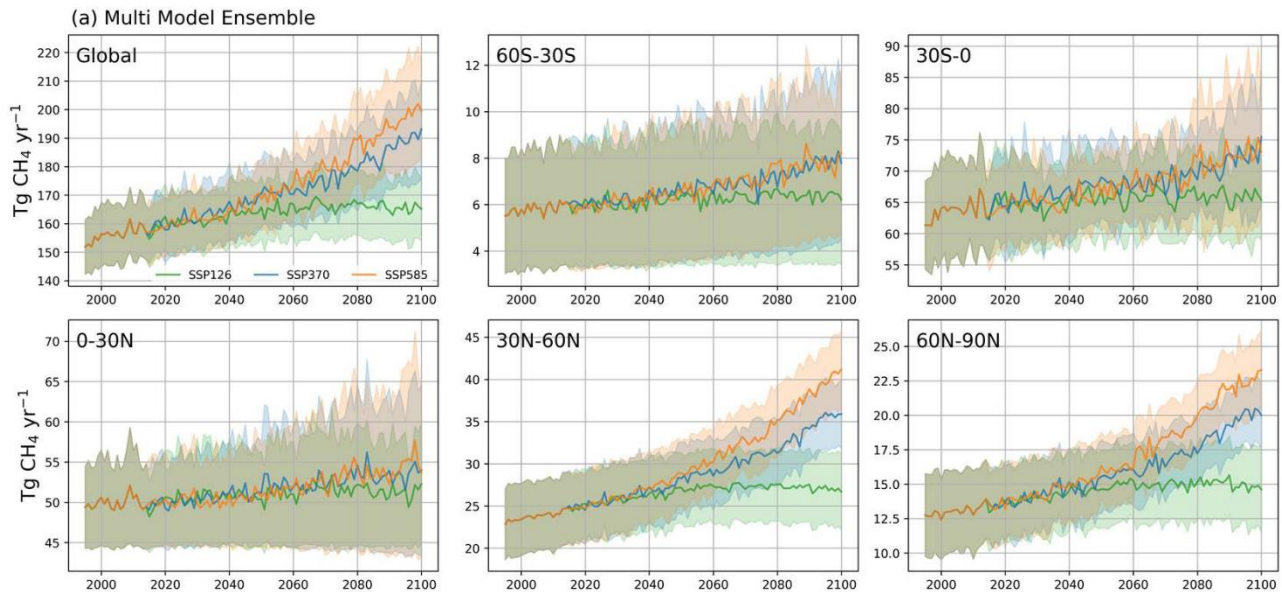


Figure 12. Model future predictions of annual wetland emissions of different regions: The solid lines represent the average methane emissions driven by 5 GCMs. The shaded areas represent the 1 $\sigma$  range of the estimates from 5 GCMs. The green, blue, and orange colors represent model predictions driven by SSP126, SSP370, and SSP585.

### **BASGRA\_N and BASGRA-YASSO**

The original BASGRA model was developed for studying grassland productivity, quality, and GHG balances in the northern latitudes (Höglind et al. 2016) and lately further extended to a BASGRA\_N version that incorporates biogeochemical cycling processes (Höglind et al. 2020). In Viikki (S6), the BASGRA\_N model was run at daily timesteps from 1 May 2022 to 25 Feb 2023 which was the grass cultivation period in the field. The meteorological drivers for the model were processed from the data collected by the in-situ instruments in the field as explained in Nevalainen et al. (2022). The model was initially run with a generic parameter set for grass. Next, using the LAI and NEE observations for the whole period, the generic parameter values were constrained.

In Qvidja (S5), we overcome the limitations of the soil model in BASGRA\_N by coupling BASGRA to the soil carbon model Yasso20 (Viskari et al. 2022), which is a five-pool litter and SOC decomposition model used also in Finnish GHG inventory and calibrated using an extensive set of global measurements. The litter inputs to Yasso consist of the fluxes of senescent leaves, stubble, and root turnover, which are directly simulated by BASGRA. In Yasso, the litter inputs are split into four fractions according to their solubility and here, we used the fractions consistent with Palosuo et al. (2015) for Finnish grasslands. The coupling, handling of organic soil amendments and

Yasso drivers are described in detail by Heimsch et al. (2024). BASGRA-Yasso was run at daily timesteps.

The simulations for the uncertainty, calibration, and validation analyses were performed on PEcAn platform (see later) from 1 May 2017 to 31 July 2023 in Qvidja. We divided the simulation period into calibration (1 May 2017 to 30 April 2021) and validation (1 May 2021 to 31 July 2023) parts. While the observations start from 2018, the year 2017 was run as a spin-up to reduce the impact of the initial state on the calibration. Meteorological drivers for 2017 were taken from Copernicus regional reanalysis for Europe (CERRA). From 2018 onwards the meteorological data collected by the in-situ instruments were used to drive the model. The joint parameter probability distributions for the Yasso part of the BASGRA-Yasso model were taken from a previous global calibration analysis (Viskari et al, 2022). The total soil carbon pool was set to the observed SOC stock (16.6 kg m<sup>-2</sup> in the 1 m layer, Heimsch et al. 2021). The partitioning of the pool into the different Yasso pools is described in detail in Heimsch et al. (2024).

### **3.4 WP4 – FMI (Liisa Kulmala) and Luke (Narasinha Shurpali)**

#### **STICS**

STICS (Scientific, Technical and Interdisciplinary simulator of soil-Crop System functioning) is a daily time-step, process-based crop model that allows variations in climate, soil and crop systems to be simulated, covering plant growth as well as fluxes of water, C and N (Beaudoin et al. 2022, Brisson et al. 2003). FMI has utilized the model especially due to the possibility of simulating undersown species together with crop, e.g., the first year of grass rotation with a cover crop. However, under this project it is mainly applied to the grass-cultivation year at Viikki. In the model, plant growth is driven by radiation intercepted by the foliage, which in an intercropped situation is divided into three components: the dominant canopy and shaded and sunlit parts of the understory canopy. The intercepted radiation is converted into biomass allocations that vary with developmental stage. Stress reduces growth, with STICS accounting for nitrogen, water, waterlogging and thermal stress. Soils interact with plants through roots, which are given as root density distribution in the soil. Heterotrophic respiration is modelled from the mineralisation of crop residues and humus. STICS was run at Viikki site on a daily time-step from 01-01-2022 to 16-11-2022. In-situ meteorological observations were used for driving the model and available soil properties are used as initial conditions for the simulations (with no spin-up). Data streams from the site, namely Net Ecosystem Exchange (NEE) and Sentinel-2 derived Leaf Area Index (LAI) are used to inform the model in a preliminary calibration exercise.

#### **L-DNDC**

The LandscapeDNDC (L-DNDC) is a process-based model capable of modelling at site and regional scales (Haas et al. 2013). The model is designed to be able to simulate grassland, arable and forest sites providing flexibility to model the changes in the land use over time. It can be run at different temporal resolutions and even runs with sub-daily time steps are possible. The L-DNDC model processes several essential fluxes simultaneously, such as carbon, nitrogen and water cycles, as well as plant development. To achieve feasible results, the model requires climate data, soil properties and, at least in the agricultural context, the management operations (e.g. fertilisation and harvesting) from the site. The simulations were run for the fields of the Ruukki NorPeat (Super 4) with the L-DNDC model (v.1.35.2) for the years 2017-2021, with the first years being considered as spin-up years. The model was run for the six plots, and these simulations were run separately due to the differences in soil texture and peat depth. The soil properties were filled in with equivalent field measurements. However, as the individual soil measurements (e.g. hydraulic conductivity) may not

cover the whole field, some of the values were subsequently modified to correspond to the dynamics seen in the observations (e.g. variability in soil moisture). The simulations were run on hourly time steps and compared with the measured data from dark chambers (respiration), EC tower (NEE, soil moisture) and satellites (LAI).

The Agri SMEAR Viikki field was also simulated using the L-DNDC model. The simulated years were 2022 and 2023 (until the end of September) and there were no spin-up years considered. Like previous L-DNDC simulations, the soil properties were filled with available field information and tuned based on the dynamics seen in the observations. The simulations were also run subdaily, but with half-hourly time steps.

### **DNDC (Denitrification-Decomposition)**

The DeNitrification-DeComposition (DNDC) model is a process-based biogeochemical model developed for quantifying C sequestration as well as emissions of C and N gases from agricultural ecosystems (Giltrap et al., 2010; Deng et al., 2020). The model consists of six sub-models, of which soil climate, plant growth, and decomposition are driven by ecological drivers, namely climate, soil, vegetation, and anthropogenic activity. These sub-models predict the soil's environmental parameters i.e., soil temperature, moisture, pH, Eh, and substances like  $\text{NH}_4^+$ ,  $\text{NO}_3^-$ , and DOC. These substances power the other three models, which are denitrification, nitrification, and fermentation. These models then predict the emissions of  $\text{CO}_2$ ,  $\text{CH}_4$ , nitrogen dioxide ( $\text{N}_2\text{O}$ ), ammonia ( $\text{NH}_3$ ), nitric oxide (NO), and dinitrogen ( $\text{N}_2$ ) from the plant-soil systems. A modified DNDC i.e., Heat exchange DNDC (HE-DNDC) was employed in this study for Anttila (S1) to simulate the surface heat exchange, C & N gas fluxes and soil frost and thaw dynamics in cold regions (Forster et al., 2022b). The HE-DNDC model was feed with daily climate data, including minimum and maximum temperatures ( $^{\circ}\text{C}$ ) and rainfall (mm), as well as humidity (%), windspeed (m/s), and solar radiation ( $\text{MJ}/\text{m}^2$ ) from the period 2000 to 2022. Although the simulations were generated for the period 2017 to 2019, the climate files from 2000 to 2016 were used as spin-up period to stabilize the soil carbon stocks in the HE-DNDC model. The model also provided with rainfall N concentrations, atmospheric  $\text{NH}_3$  and  $\text{CO}_2$  concentrations, and annual increases of atmospheric  $\text{CO}_2$ , although model default values can be used when such information is not available. In addition, we used measurements of actual snow depth to drive the model (Deng et al., 2014). Using measured snow depth in this way improves the surface energy balance and hence the simulated soil temperature and water filled pore space (WFPS  $\text{cm}^3/\text{cm}^3$ ). Soil input data include soil properties according to the USDA soil classification system, as well as information on initial soil organic carbon (SOC), pH and other soil physiochemical factors. The input parameters of farming management practices, including crop types, planting and harvest dates, tillage, residue return, and irrigation, were taken from Li et al (2023). Simulations were conducted for both sides i.e., fertilization treatments to compare them with each other and with the actual measured data.

### **PEcAn Modelling platform (T4.2)**

The three of the models used in the project; STICS, L-DNDC and BASGRA-Yasso (including the BASGRA\_N version) were coupled to an open-source ecological informatics toolbox called PEcAn (Predictive Ecosystem Analyzer, pecanproject.org, Lebauer et al. 2013). Coupling a simulation model to the PEcAn platform entails writing wrapper scripts that pre- and post-process model inputs and outputs, as well as a script that takes control of the model configuration and execution. This way PEcAn standardises and automates model runs and model-data synthesis activities such as sensitivity and uncertainty analyses, as well as calibration of model parameters. PEcAn adopts a

Bayesian approach where uncertainty about the values of model parameter values and initial conditions are represented as prior distributions, and combinations of different parameter and initial condition values are sampled from these prior distributions to run the model in ensembles to propagate uncertainty in model input to model output. These priors then can be constrained as observations become available. The uncertainty in the BASGRA-Yasso parameter values was propagated to the model outputs by running the model 1000 times with a different parameter vector drawn from the probability distributions on parameters. The parameters that contribute most to the model output uncertainty for the LAI and NEE variables were chosen for targeting in a Bayesian calibration. Out of 20 BASGRA-Yasso parameters we varied in total, four of them contributed most to the model output uncertainty: . These parameter values were estimated indirectly through an inverse method using Bayesian calibration, informed by LAI and NEE data streams jointly. For the NEE data stream used in calibration, we further screened out the flux data to include only days when more than 50% of the measurements were available because the flux data needed to be gap-filled for aggregating into daily values (to match the model time-step). In other words, days that had more gap-filled than measured data points were not used to inform the calibration, which resulted in 377 daily NEE observations used in calibration. The details of the calibration are introduced in Heimsch et al. (2024)

STICS and L-DNDC models are more complex, and the generalization of their execution is more intricate as these models can simulate many species and management options. In addition, their coupling to the PEcAn platform is more recent and therefore still under development. Preliminary sensitivity and calibration analyses through PEcAn are conducted with these models at the Viikki site with respect models' LAI and NEE outputs. Results (not shown here) indicated that similar processes contribute to the output uncertainties similarly for the two models and these uncertainties can be constrained using satellite derived LAI observations and in-situ flux measurements. The analyses will be repeated at the end of 2024 for more sites with the improved coupling of both models. Last but not the least, the basic coupling of the STICS model was co-tested together with an FMI & LUKE workshop at the Anttila site. In this demonstration, LUKE team set up the PEcAn system on CSC resources and went through a hands-on follow-along coding activity using STICS through PEcAn, lead by the FMI team. This activity was an example of a case where institutes leveraged one another's open-source code development and applied it on their research site.

## **A review of the agroecological modelling situation in the boreal region**

Forster et al. (2022) provided a crucial review on “**Use, calibration and verification of agroecological models for boreal environments**” in 2022. The main idea of the paper was to review the Agroecological model performance across boreal environment and management systems. There is considerable uncertainty regarding the performance of models designed for temperate and tropical zones when applied in boreal conditions, as few models are specifically developed for these areas, raising concerns about their accuracy in simulating agricultural productivity, carbon and nitrogen cycles, and greenhouse gas emissions. The review identified a dearth of modelling studies in boreal regions, with the publication of three or less papers per year since the year 2000, constituting a significant research gap.

Forster et al. (2022) emphasize the importance of models like IFSM and BASGRA\_N in grassland production and DNDC for predicting soil N<sub>2</sub>O and NH<sub>3</sub> emissions. No model outperformed all others, strengthening the case for ensemble modelling. They advocate for the use of ensemble modelling to improve reliability and accuracy, as no single model outperforms others across all metrics. They conclude that existing agroecological models warrant further evaluation and improvement specifically designed for boreal systems.

The review offers several recommendations for future modelling work:

1. **Evaluation of individual models** using field data measured for grassland production, soil C and N cycling, and GHG emissions for multiple boreal environments.
2. **Model Intercomparison:** Evaluate multiple models using the same datasets within boreal zones.
3. **Identification of sub-model processes underpinning superior model performance.**
4. **Opportunities for Parsimonisation:** Simplify models to the appropriate level while maintaining coherence.

By integrating the insights and methodologies from Forster et al. (2022), the NC-Grass project aimed to adapt and validate models such as DNDC, BASGRA, and STICS to local conditions. This initiative sought to enhance simulation precision and promote sustainable agricultural practices in boreal environments.

### **Model performance evaluation and improvement (T4.1)**

#### **BASGRA**

Parameter calibration improved the performance of BASGRA-Yasso in terms of both uncertainty reduction and accuracy in the calibration and validation periods (Figure 133). After calibration, annual balances of NEE agreed with observations for both the amount and the trend across the years (14). However, when NEE was partitioned into NPP and respiration, although the partitioned observations still fell within the model confidence intervals, a particular discrepancy remained for the year 2018 where BASGRA-Yasso tended to underestimate these components for 2018 after the calibration (Figure 1). Another remaining discrepancy occurred for the 2021 harvest which the model underestimated, even though the predicted single June 2021 harvest was the all-time highest. Overall, the model was mostly able to reproduce the observed dynamics and annual carbon balances of the field.

In general, the BASGRA\_N simulations succeeded to reproduce the observations in Viikki (Figure 1) but overestimated the sink in May 2022 when the observations showed a net release of CO<sub>2</sub>.

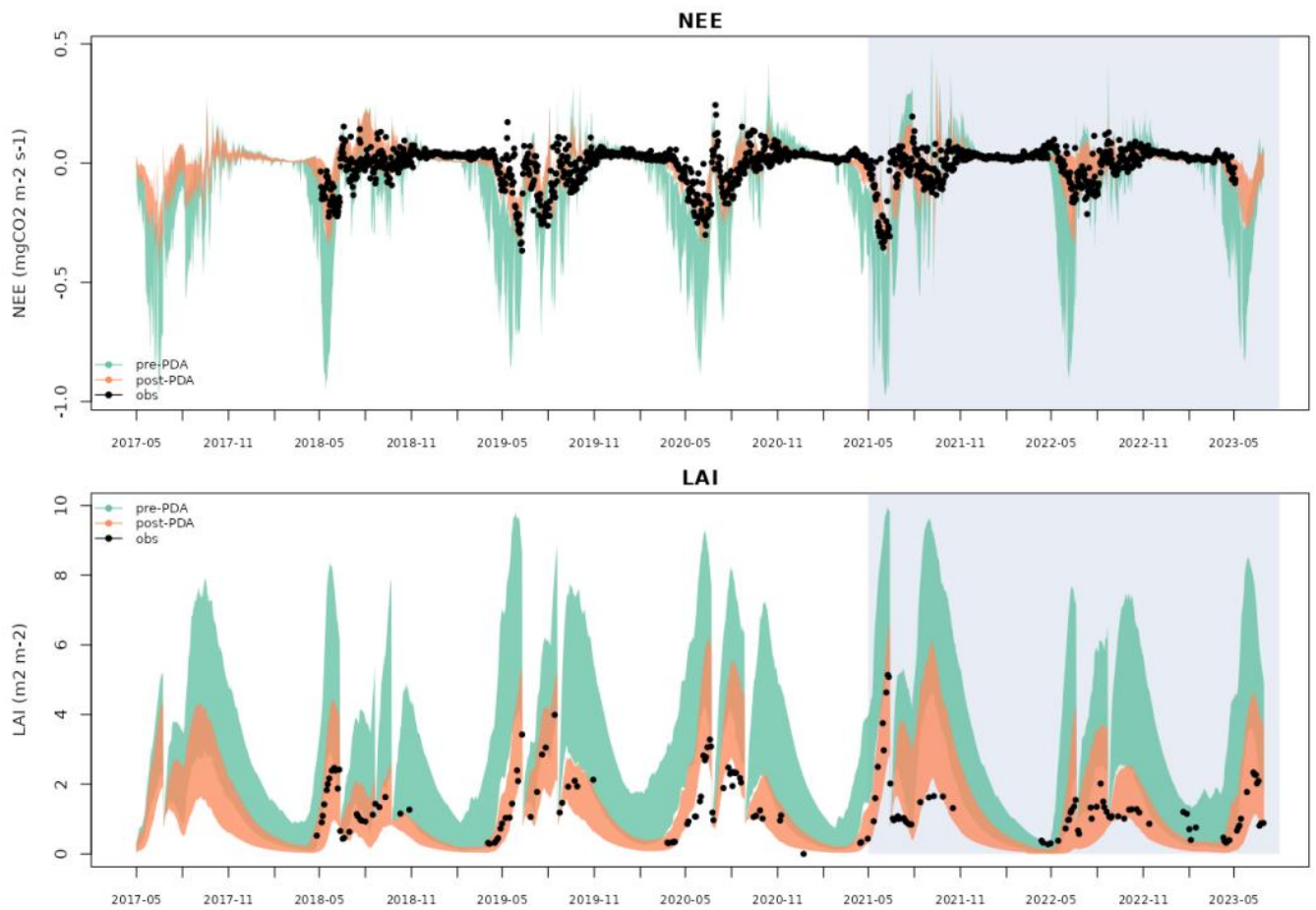


Figure 13: Observed (black dots) and simulated (lines) net ecosystem exchange of CO<sub>2</sub> (NEE, above) and leaf area index (LAI, bottom). Both panels include simulations by BASGRA-Yasso before (green) and after (orange) calibration in Quidja (S5). The shaded areas indicate the out-of-sample (validation) period from 1 May 2021 to 31 July 2023. Figure from Heimsch et al. (2024).

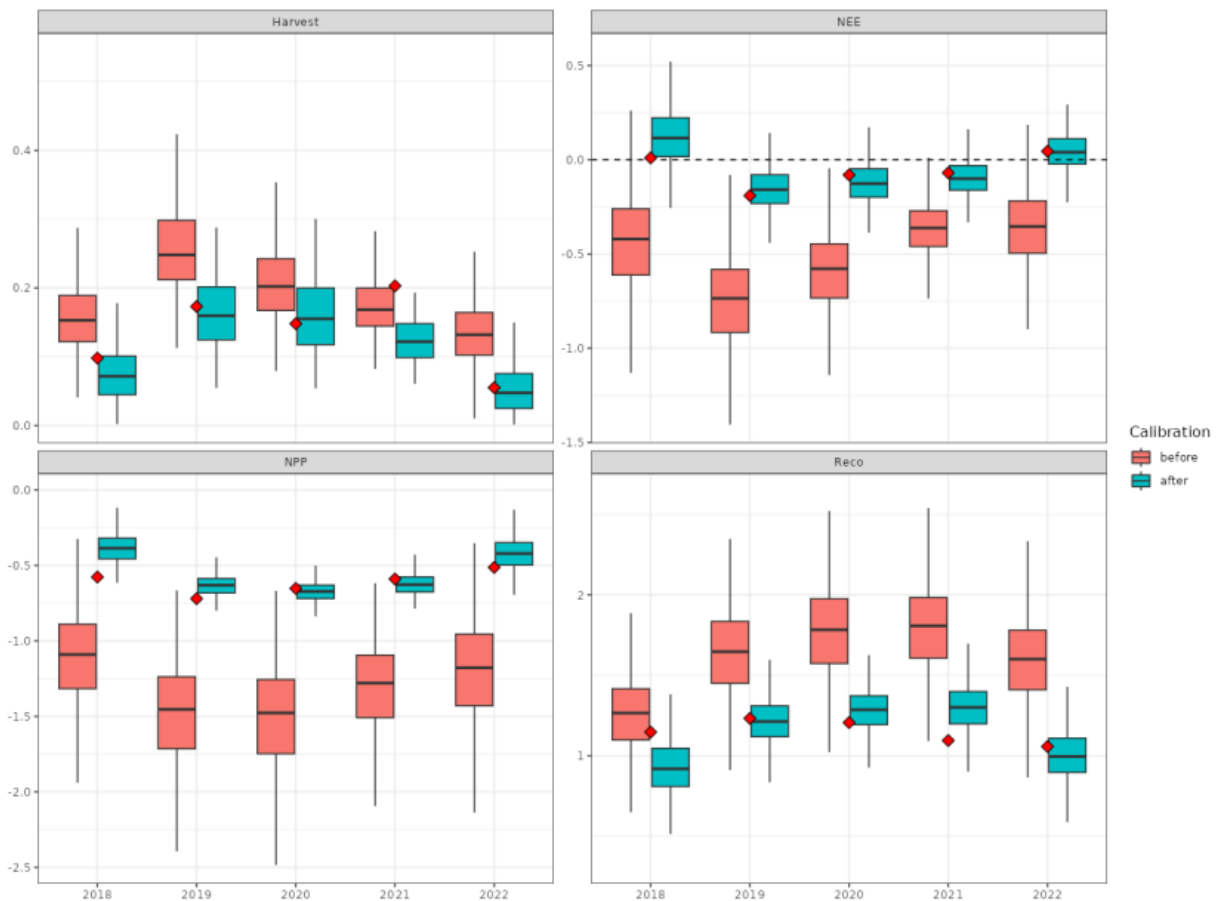


Figure 14: Annual (from 1 May to 30 Apr) balances of harvest, net ecosystem exchange (NEE), net primary production (NPP), and respiration (Reco) by BASGRA-Yasso before (pink) and after (blue) calibration in Qvidja (S5). The red diamonds represent the annual balance calculation from the observations. NPP is assumed to be half of GPP. Figure from Heimsch et al. (2024).

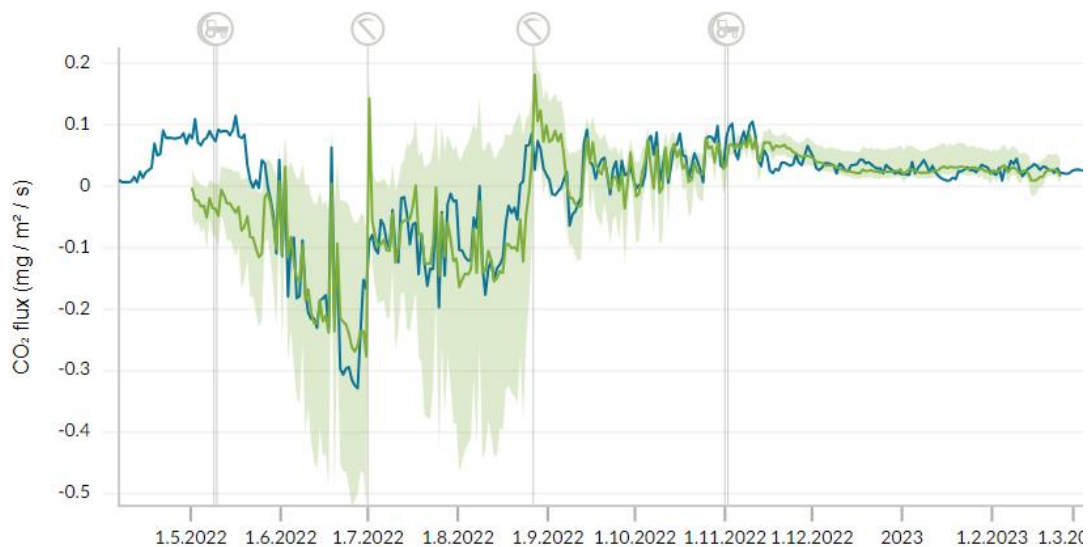


Figure 15: Observed (blue) and simulated with BASGRA (green) mean daily net CO<sub>2</sub> flux (NEE) in Viikki (S6) grassland during April 2022 and March 2023. The first tractor symbol indicates the timing of fertilization and the second tillage. The sickles indicate the timing of harvests.

## STICS

In general, the STICS succeeded to reproduce the LAI and NEE observations in Viikki (Figure 16) also during May when BASGRA\_N and L-DNDC (see later) overestimated the NEE. The normalized RMSE for the post-calibration ensemble median was 46.2 and 48.7, for LAI and NEE respectively.

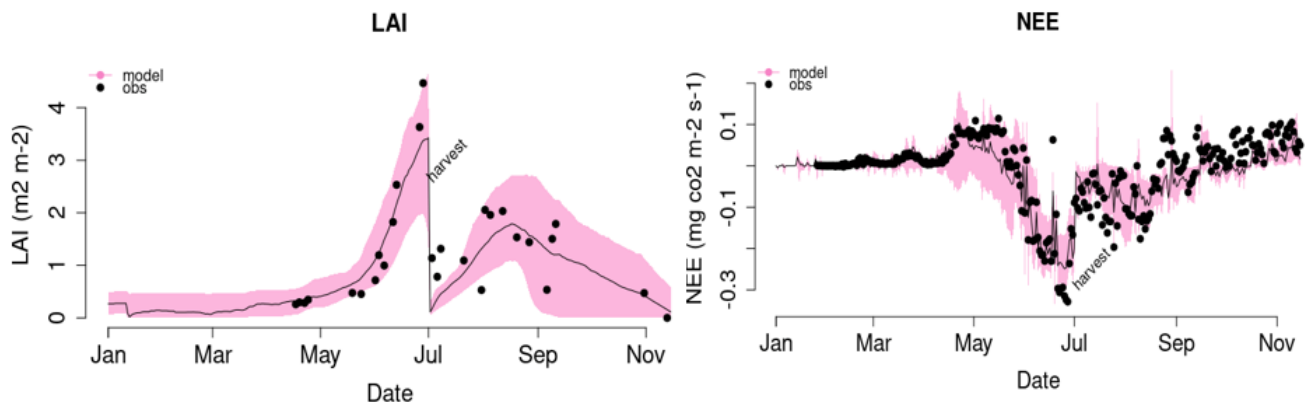


Figure 16: Observed (black dots) and simulated with STICS (pink, ensemble median solid black-line) mean daily LAI (left) and net CO<sub>2</sub> flux (NEE, right) in Viikki grassland (S6) in 2022. Timing of harvest is marked on the figures.

## Landscape-DNDC

In Viikki, the simulated NEE results were aggregated to the daily level and the mean value of the aggregated results is compared with the observations for the year 2023 (Figure 17). Both the seasonal and daily dynamics are similar between the simulated and the observed time series, although there are higher positive values (respiration) at the beginning of the year in the observations and more photosynthesis in the simulations during the growing season.

The simulated mean daily net CO<sub>2</sub> exchange (NEE) for all plots in Ruukki NorPeat followed the dynamics in the observations (Figure ). However, the model did not produce such respiration peaks as in the observed data after the mowing periods (17. - 20.6. and 11. - 14.8. in 2020, 22. - 28.8. and 16.-17.8. in 2021). Furthermore, on a sub-daily level, the diurnal variability in the net exchange simulations seems to be generally restrained, especially during the growing season.

The seasonal variability of the simulated leaf area index (LAI) generally followed the trend obtained from the satellite measurements (Figure ). However, there were some cases where the observed and simulated results differed. For fields 1–4, which were the fields with new (young) grass, the simulated LAI values started to increase early in 2020 compared to the values obtained from satellite observations (Figure ). For fields 5-6 with older grass, the fit was better in the early season. In addition, there were notably higher observed LAI values especially in the year 2021 and in the second cut in 2020.

In the observations of soil moisture, we can see the soil moisture drop during the growing seasons and in simulations we can see the similar effect (Figure ). In the growing season, even though there is a lot of fluctuation, simulated soil moisture does not vary as much in magnitude as the observed values.

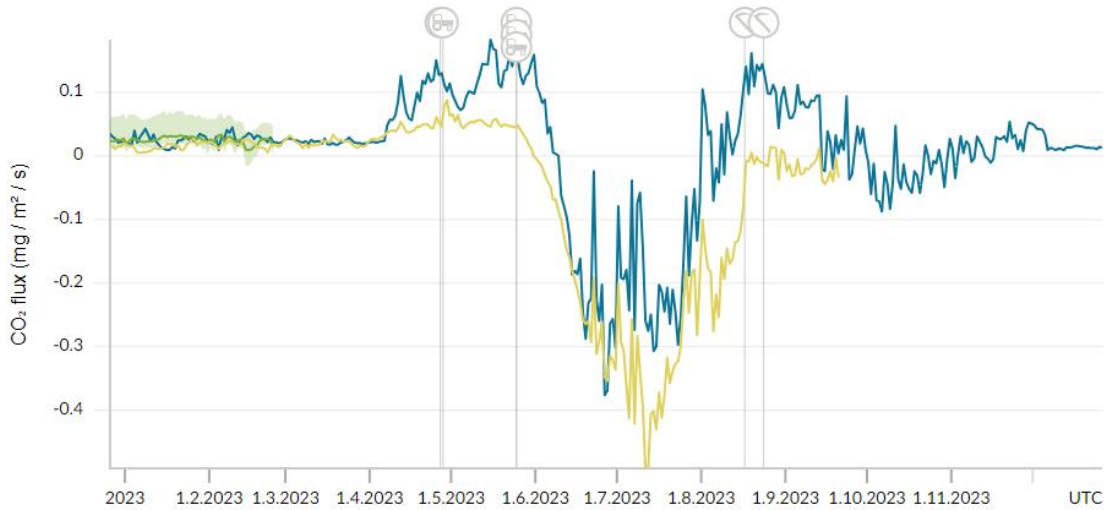


Figure 17: Observed (blue) and simulated with L-DNDC (yellow) mean daily net CO<sub>2</sub> flux (NEE) in Viikki grassland (S6) in 2022. The first tractor symbol indicates the timing of fertilization and the second tilling. The sickles indicate the timing of harvests.

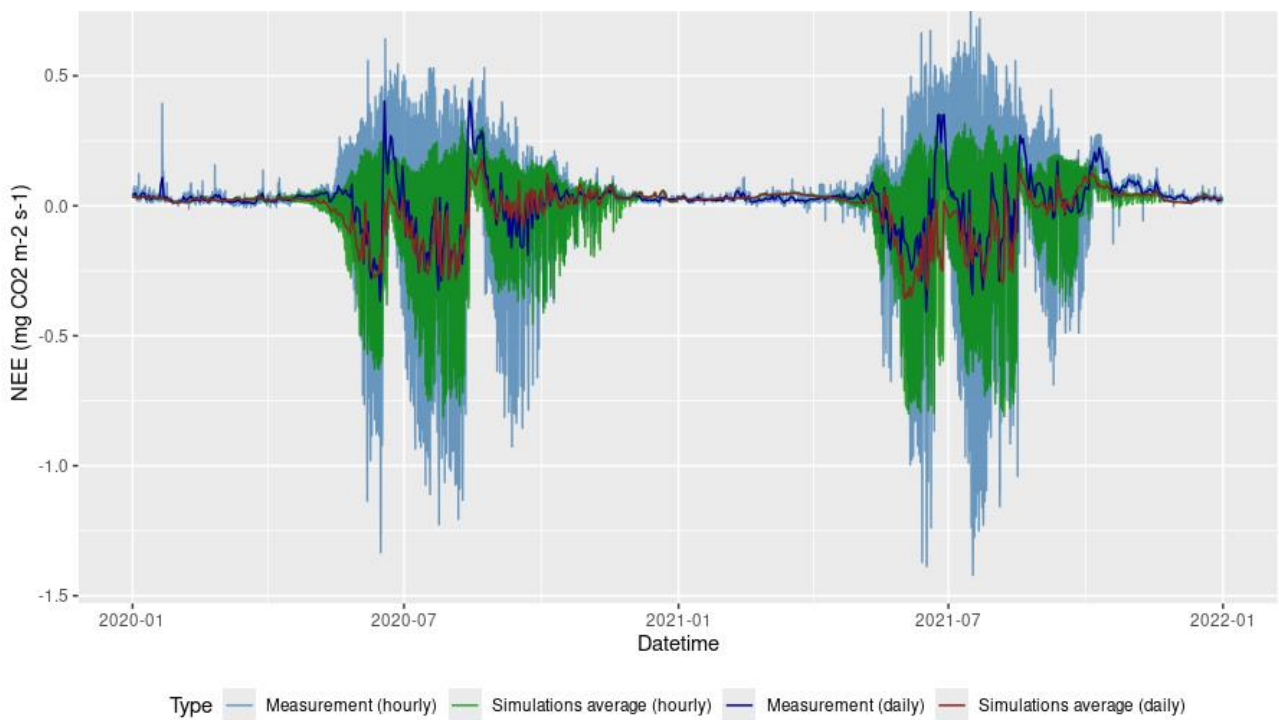


Figure 18: Simulated (green and red) and observed (light and dark blue) momentary and daily mean net ecosystem CO<sub>2</sub> exchange (NEE) between grassland and atmosphere in the Ruukki NorPeat (Super 4) in 2020-2021. Negative values indicate net uptake (sink) and positive values release (source) of atmospheric CO<sub>2</sub>. The sharp changes during the growing seasons are due to mowing events.

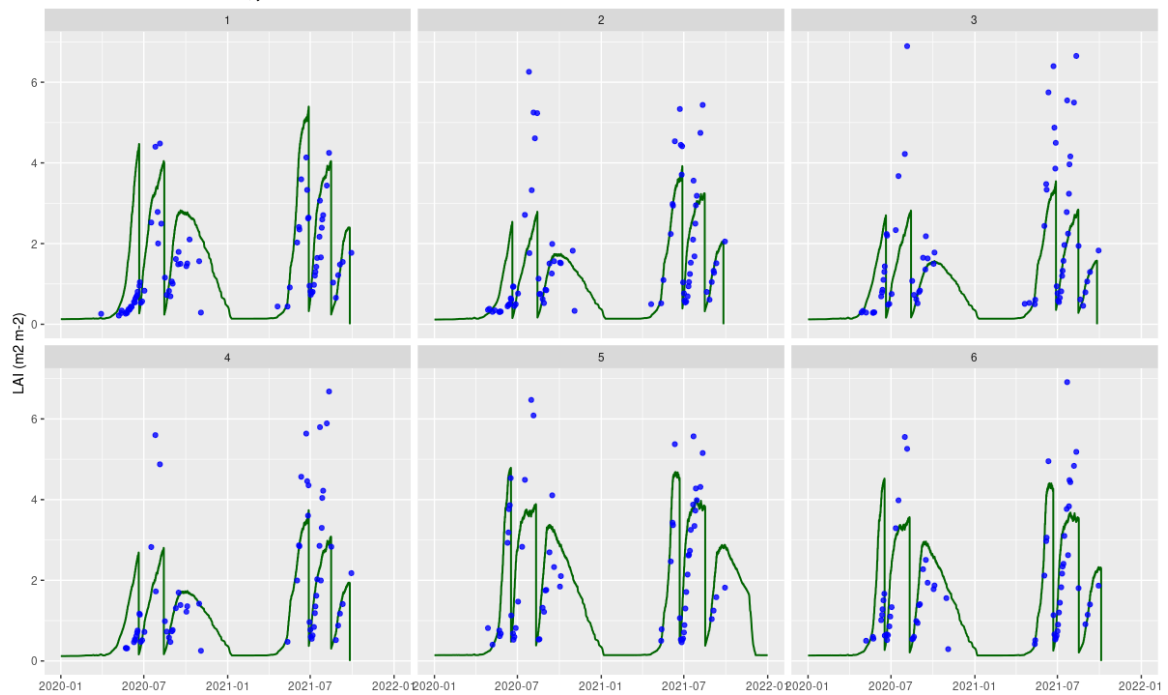


Figure 19: Simulated (line) and observed (dots) leaf area index (LAI) in the six different plots at Ruukki NorPeat (Super 4) in 2020-2021. The sharp changes during the growing seasons are due to mowing events.

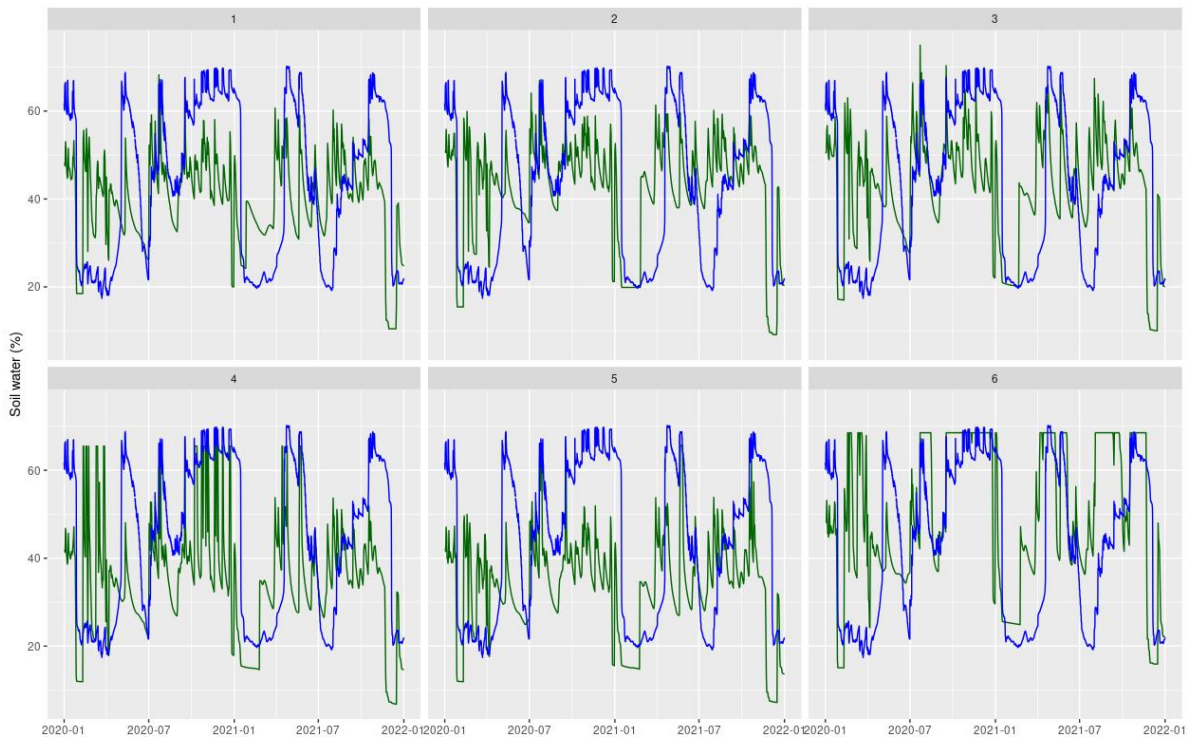


Figure 19: Simulated (green) and observed (blue) soil water content (%) in the six different plots at Ruukki NorPeat (Super 4) in 2020-2021. The observations are collected in the middle of the field and are not plot-specific.

## DNDC (Luke)

The evaluation of simulated versus measured CO<sub>2</sub> exchange and soil microclimate parameters revealed varying levels of HE-DNDC model performance (Table 10). For GPP, there was a good correlation  $\rho$  (Spearman's rank correlation) between simulated and measured data, though MAE (Mean Absolute Error) was poor, RMSE (Root Mean Square Error) was fair, and the model pBias% (Percent bias) underestimated and scored poor. For NEE, there was a good  $r$  correlation between simulated and measured data, though MAE was poor, RMSE was fair, and the model scored good overall, with a small pBias% underestimate. For Reco, there was a good  $r$  correlation between simulated and measured data, though MAE was poor, RMSE was good, but model pBias% underestimated and scored poor (Table 10).

Table 10: Evaluation results for simulated versus measured Gross Primary Productivity (GPP), Net Ecosystem Exchange (NEE) and Ecosystem Respiration (Reco) and soil microclimate. Water filled pore spaces (WFPS) stands for soil water and the 'Mean score' column represents the overall assessment when all four measures are accounted for.

	$\rho$	MAE	RMSE	pBias%	Mean score
GPP (kg C/ha)	0.80 (p < 0.001)	21.3	35.1	-20.7	Fair
NEE (kg C/ha)	0.72 (p < 0.001)	16.6	26.6	-14.2	Fair
Reco (kg C/ha)	0.85 (p < 0.001)	10.9	14.2	-22.8	Fair
Soil temp (°C)	1.00 (p < 0.001)	0.1	1.2	18.2	Excellent
WFPS (cm <sup>3</sup> /cm <sup>3</sup> ) 5cm	0.73 (p < 0.001)	0.1	0.1	-11.2	Excellent
WFPS (cm <sup>3</sup> /cm <sup>3</sup> ) 20cm	0.25 (p < 0.001)	0.1	0.1	-5.0	Good

For soil temperature there was a correlation  $r$  score of excellent, MAE was excellent, RMSE was excellent and pBias% scored fair, and showed that the model overestimated compared to measured data. Soil water (WFPS) at 5 cm scored "good"  $r$  for Spearman's correlation, MAE was excellent, and RMSE was also excellent, while there was a small, but good underestimation for pBias%. For WFPS at 20 cm there was a poor  $r$  correlation, whereas MAE was excellent and RMSE was excellent, whilst there was only a small pBias% underestimation, which scored excellent (Table 10).

HE-DNDC fairly predicted the carbon stocks and showed no difference between the organic and mineral input treatments in predicting GPP. However, slight variations were observed in NEE and Reco. Although the prediction flow aligns with that shown in Figure , there are some discrepancies during certain events, such as at the beginning of the growing season and at the first cut of the grass, where the predictions are in quite opposite when compared to the measured values. However, during the growing season, the model predictions are in line with the measured values. In 2019, the model predictions started a month early, while the measured data was recorded from June, as the crop was sown on June 4<sup>th</sup>. In June, the model overestimated Reco, which may be due to events like gap filling that took place during the early growth stages as the crop was established in 2019. The model recorded higher Reco in the Norg treatment compared to the Nmin treatment.

The purpose of using the HE model to capture the heat exchange near the ground surface, which was achieved, as the HE-DNDC model accurately captured the surface soil temperature at 5 cm (Figure 1). However, during winter the model predicted sub-freezing temperatures (below 0°C), while the measured data recorded surface temperatures as 0°C, not below that. Additionally, there were discrepancies in predicting the water-filled pore space (WFPS) at 5 cm and 20 cm, with the

model showing several instances of overestimation and underestimation compared to the measured WFPS. Further work is being carried out to refine the predictions and align them more closely with the measured data.

Simulated biomass (DM kg/ha) under Nmin and Norg inputs significantly exceeded measured values during 2017-2019, simulated mean biomass was 4517 kg/ha for both treatments, compared to measured means of 3117 kg/ha (Nmin) and 3026 kg/ha (Norg). HE-DNDC simulations showed notable deviations, particularly during second harvests in both the treatments (Figure 2, Figure). Simulated values exceeding the measured values by approximately 63% for Nmin and 120% for Norg treatments in 2017, and approximately 158% for Nmin and 161% for Norg treatments in 2018. This confirms that the model might not accurately predict biomass levels during certain periods, like the second harvest. It is possible that the discrepancy arises from the model's assumption of perennial grass as the crop type, which may not accurately reflect the actual conditions where three grasses, including a leguminous grass, are grown in a mixed cropping system. Developers must refine the DNDC model to better represent mixed cropping systems for more reliable biomass yield predictions, improving its agricultural management applications.

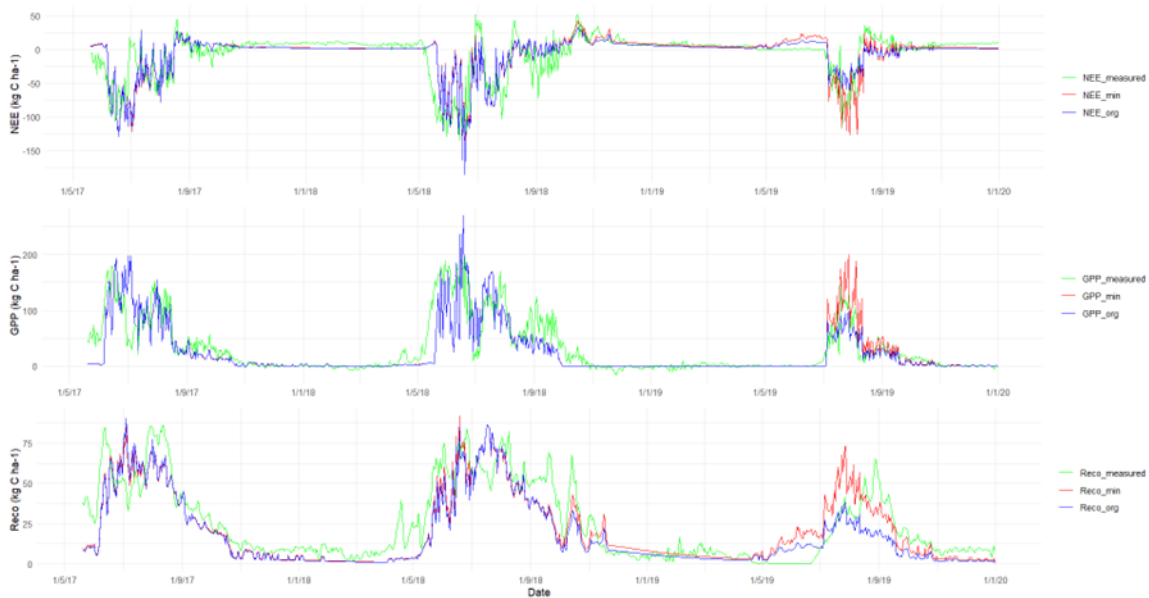


Figure 20: Comparison of Simulated and Measured (min, org) Gross Primary Productivity (GPP), Net Ecosystem Exchange (NEE) and Ecosystem Respiration (Reco) at Anttila (S1) with mineral (min) and organic (org) fertilization



Figure 1: Comparison of simulated (mineral, organic) and measured soil temperature and water filled pore space (wfps) at Anttila (s1) over three growing seasons.

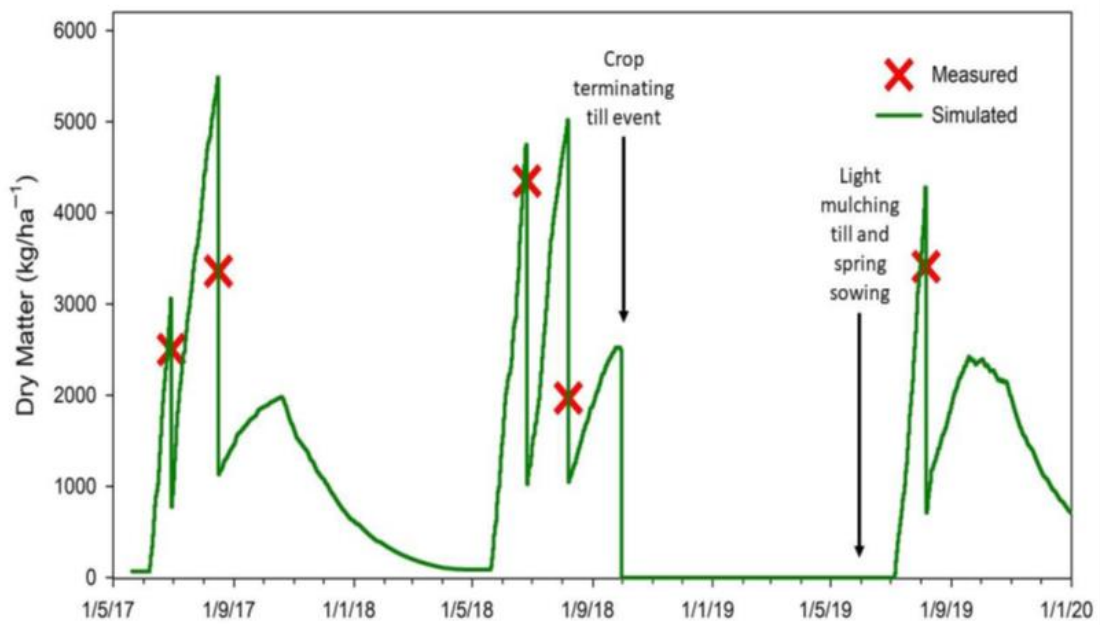


Figure 2: Comparison of simulated (—) and measured (X) biomass production (DM kg/ha<sup>-1</sup>) for Nmin treatment at Anttila (S1) during the growing seasons from 2017 to 2019. The black arrows represent ‘ploughing event’ and ‘tillage and spring sowing’.

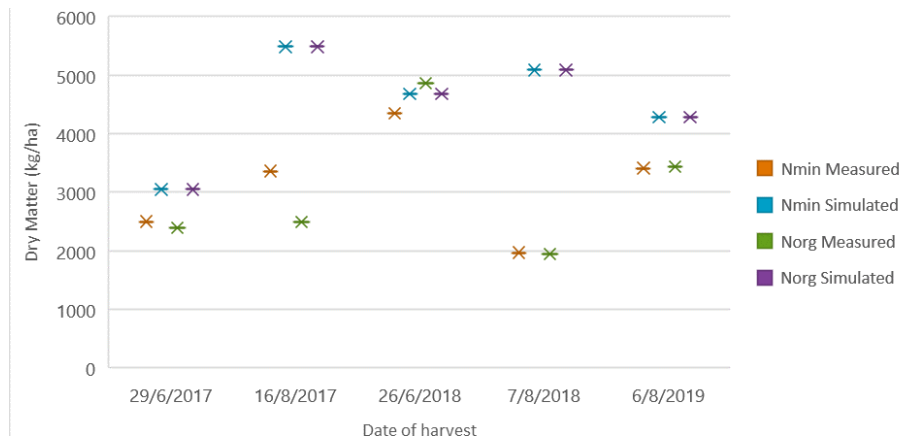


Figure 22: Comparison of Measured and Simulated biomass production (DM kg/ha) for Norg and Nmin Treatments at Anttila (S1) in 2017-2019.

Table 11 compares simulated and measured carbon fluxes, revealing insights into ecosystem productivity and carbon exchange dynamics under different nutrient inputs. GPP simulations closely aligned with measured data across Norg and Nmin treatments, albeit showing slight underestimations in 2018 and overestimations in 2019. However, NEE and Reco simulations exhibited greater variability and discrepancies, particularly in 2018. While the model effectively captured primary productivity dynamics, discrepancies in NEE and Reco simulations indicate areas for model refinement to better understand carbon exchange processes.

Table 11: Comparison of total annual Gross Primary Productivity (GPP), Net Ecosystem Exchange (NEE) and Ecosystem Respiration (Reco) for a treatment if organic fertilization (Norg) and mineral fertilization (Nmin) in Anttila (S1) in 2018 and 2019.

Evaluation years	Measured data	Simulated Norg treatment	Simulated Nmin treatment	Difference between Measured and Norg treatment	Difference between Measured and Nmin treatment
<b>GPP (T C/ha/ yr)</b>					
2018	14.79	10.99	11.02	3.81	3.77
2019	4.36	3.40	5.71	0.96	-1.35
Mean	9.58	7.19	8.37	2.28	1.21
<b>NEE (T C/ha/ yr)</b>					
2018	-3.64	-2.05	-2.36	-1.59	-1.28
2019	0.22	-1.07	-0.62	1.29	0.84
Mean	-1.71	-1.56	-1.49	-0.15	-0.22
<b>Reco (T C/ha/ yr)</b>					
2018	11.15	8.94	8.66	2.21	2.50
2019	4.58	4.64	5.09	-0.06	-0.51
Mean	7.87	6.79	6.88	1.08	0.99

### Carbon sequestration at the different sites (T4.3)

Table 12 lists the simulated annual NEE levels for four study sites for some study years. Many of the simulated annual NEE values are negative, indicating that net photosynthesis (GPP) has exceeded natural CO<sub>2</sub> emissions (TER or Reco). However, this is unlikely to be the case in Ruukki, for example, where the observed balance is positive, i.e. peat decomposition is greater than plant carbon sequestration (Gerin et al. 2023). Further model development and calibration is therefore needed to estimate the actual annual carbon sequestration with these models.

Table 12: Examples of the simulated net ecosystem exchange of CO<sub>2</sub> (NEE) at the different super sites. Simulations were done with HE-DNDC in Anttila, with L-DNDC in Ruukki and Viikki and with Basgra-Yasso in Qvidja.

	Anttila (Nmin)	Anttila (Norg)	Ruukki	Qvidja	Viikki
Year	2018	2018	2020	2022	2022
Sim. NEE (g C m <sup>-2</sup> )	-191	-260	-361	47	-320

### Grassland production in Finland – Spatial and Temporal variability – Projected climate (Luke – Daniel Forster and Narasinha Shurpali)

With the effects of climate change being felt, there is increasing pressure to expand agricultural operation into northern latitudes, however this is not without risk. Such expansion may exacerbate loss of terrestrial carbon (C) stores if undertaken without careful strategic planning. Agroecological models are fundamental in forecasting the impacts of climate and contrasting management scenarios, yet there is a dearth of research aimed at improving the rigour underpinning models for boreal regions. Here, we build on previous work in using the model DNDC (DeNitrification-DeComposition) to predict long-term effects of land management and climate change scenarios (Representative Concentration Pathways or RCPs) on crop production, soil carbon stocks and C fluxes from 1980 to 2100 (Figure 23). We used a random forest (RF) model to determine importance of underlying model mechanisms. Under both RCPs, C fluxes increased towards the end of the century, with soil carbon stocks increasing from 89.6 t C ha<sup>-1</sup> during the baseline to 114.2 and 111.1 t C ha<sup>-1</sup> by 2100 under RCP 2.6 and 8.5 respectively, while NEE (Net Ecosystem Exchange) increased from -3.1 t C ha<sup>-1</sup> yr<sup>-1</sup> historically to -3.65 and -4.7 t C ha<sup>-1</sup> yr<sup>-1</sup>. Influential factors governing model outputs included air temperature, soil organic P, NO<sub>3</sub>, soil water and labile P, while climate change scenarios (RCPs) were of lesser importance. We contend that pastoral operations may represent a sustainable option contributing to regional food security while enhancing soil carbon stocks.

### Integrated farming systems modelling (T4.4)

Task 4 of the WP4 was to evaluate the Integrated Farming Systems Modelling (IFSM) developed for farming systems in the USA by Alen Ritz (one of the international advisors to the project). We tried evaluating IFSM for Finnish farming conditions. This model was initially developed as an educational tool with specific midwestern farming systems in mind. Dr. Daniel Forester, the modelling postdoc hired in the project, found that this model is not portable to conditions outside of its development and We decided not to spend any more time on evaluating this model. Instead, Dr. Tulasi Thentu who is now hired as a modeler in Luke in place of Daniel Forster (currently in Japan) is currently working on Manure DNDC, a model suited for grassland and livestock production with biogas generation from livestock and agricultural residues.

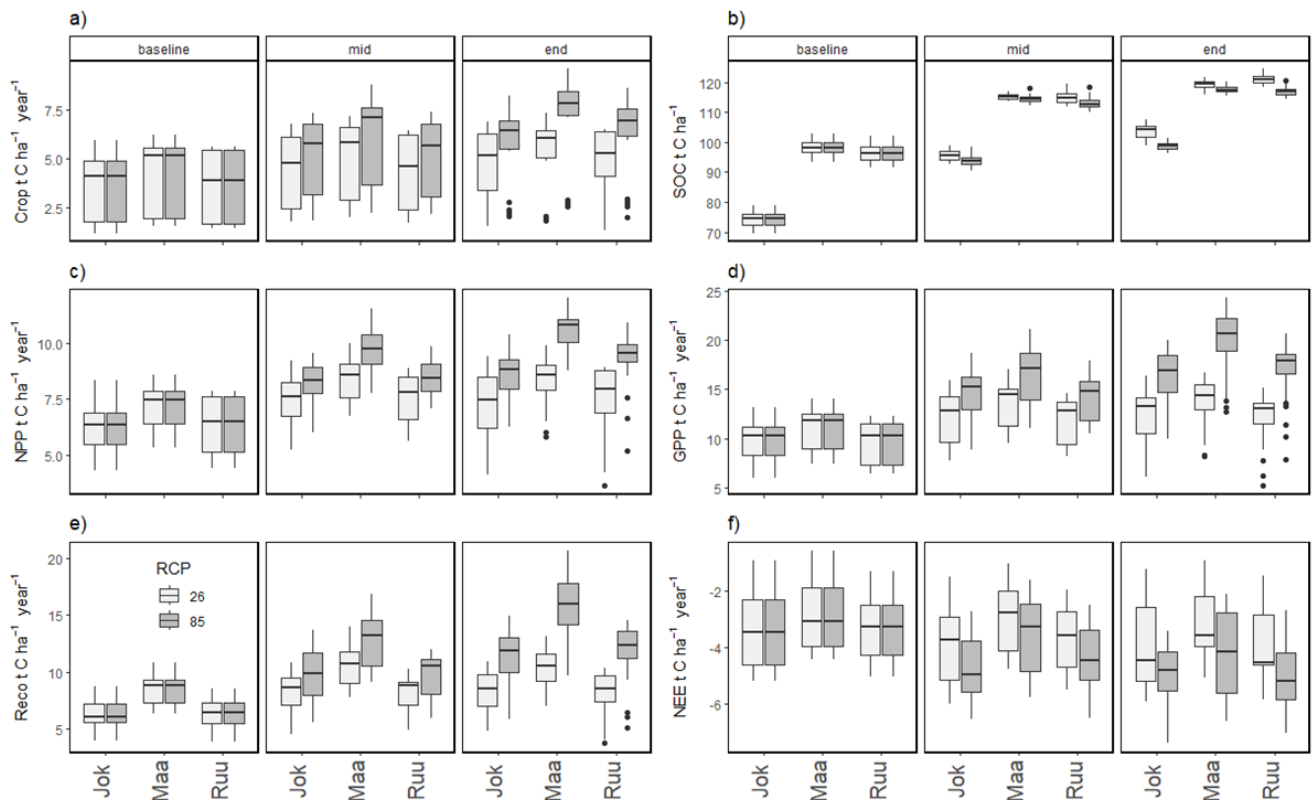


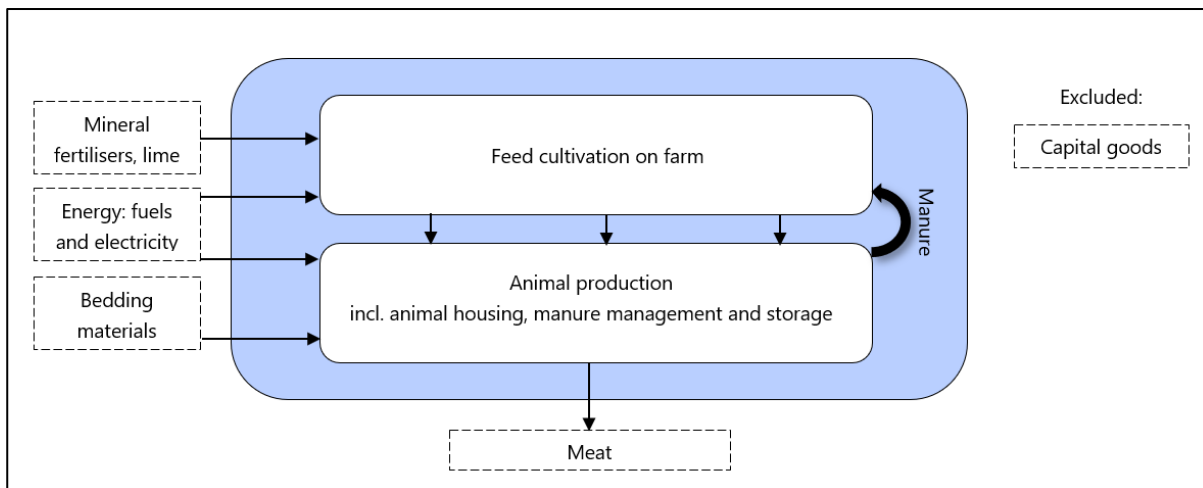
Figure 23: Summary figures of (a) crop biomass, (b) SOC, (c) NPP, (d) GPP, (e) Reco, and (f) NEE across time periods, locations, and between RCP scenarios (baseline, mid, end) and locations (Jok = Jokioinen, Maa = Maaninka, Ruu = Ruukki), with RCP scenarios 2.6 and 8.5 in light and dark grey respectively.

### 3.5 WP5 – Life cycle assessment (Luke – Annina Lehtilä, Pooja Yadav)

In this working package, the risks related to grass silage-based cattle production were assessed from environmental, social, and economic points of view. Furthermore, the changes in risks following changes in management methods were estimated.

#### Environmental assessment

Environmental risk assessment was conducted by applying the life cycle assessment (LCA) methodology. According to LCA principles, emissions were estimated from cradle to farm gate. Thus, emissions from input production (e.g., fertilisers and fuels) to emissions occurring at farms (from fields, animals, and manure) were considered, including related transports. The system boundary of the assessment is illustrated in **Fig. 24**.



**Figure 24.** System boundaries used in the study.

The LCA was conducted using Luke’s EnreBeef model (Hietala et al., 2021). EnreBeef version for dairy breed bull was chosen the assessment. Impact categories included were climate impact, eutrophication, and acidification.

The data used in the modelling consisted of ProAgria Parcel Register data (years 2015–2022), Luke’s Taloustohtori data (Luke, 2023), NC-grass and other Luke’s field experiments, relevant scientific literature and background data embedded in EnreBeef. The most important input data for the model is described in **Table 13** (for the baseline scenario).

**Table 13.** The most important input data for the scenario farms in East and South Finland in the baseline scenario.

		<b>East</b>	<b>South</b>
Cultivation area	ha/animal*	0.81	0.73
Share of silage grass out of the cultivation area	%	51	51
Share of barley out of the cultivation area**	%	49	49
DM intake (full lifetime)	DM kg/kg beef	12.2	12.2
Share of grass silage out of DM intake	%	60	60
Share of barley out of DM intake	%	40	40
Share of organic soils	%	4	11
Share of mineral soils (clay and coarse)	%	96	89
Grass yield	kg DM/ha	6068	6749
Barley yield	kg DM/ha	3500	3883
Grass N fertilisation***	kg N/ha	130–142	188–192
Barley N fertilisation***	kg N/ha	60–79	77–97

\* Full life time of the animal accounted

\*\* Also barley as cover crop of established grass ley.

\*\*\* Mineral fertiliser N + manure total ammoniacal N. Total rate depending on soil type.

Modelling was conducted for two locations – South Finland and East Finland – differing in the share of soil types and yield rates. The baseline scenarios represented the typical dairy-breed bull beef

production in the two regions. To assess the effect of different management methods on the life-cycle environmental impact of beef, a total of eight different scenarios were created (in addition to the baseline scenario).

Scenarios:

**1) Increased grass cut height**

Increased from 6 cm to 12 cm. The effect on yield rate, mineral soil C sequestration and N<sub>2</sub>O were included, based on NC-grass measurements and Yasso07 modelling.

**2) Increased yield on mineral soils, organic soils excluded from feed production**

Silage grass and barley cultivation was intensified (yield increase of 9–15 %) to exclude organic soils from feed production.

**3) Cover crops added for barley**

Cover crop species assumed to be white clover (*Trifolium repens*). Effects on mineral soil C sequestration, N<sub>2</sub>O emissions and N leaching were included, as well as reduced synthetic N fertiliser use.

**4) Increased water table level**

On organic soils cultivated with grass, the water table level was assumed to be increased from ~80 cm to ~30 cm with an adjustable draining system. Estimates of GHG emission reduction were based on IPCC (2014) and Regina et al. (2015).

**5) Organic soil fields used for grasses only**

Instead of cultivating part of organic soils with barley, only grass was cultivated on organic soil fields. Estimates of GHG emission reduction were based on emission factors used in the GHG inventory of Finland (Statistics Finland 2023).

**6) Increased yield, high**

Yield estimates (silage grass, barley) used represented 25 % of the highest yields recorded in the ProAgria data.

**7) Increased yield, very high**

Yield estimates (silage grass, barley) used represented 5 % of the highest yields recorded in the ProAgria data.

**8) Increased silage to concentrate ratio**

The amount of silage in total DM intake of animals was increased from 60 to 80 %.

The climate impact, eutrophication, and acidification in different scenarios in South and East Finland were compared with the baseline model. The changes in the assessed environmental impacts were classified as neutral, decreased, and increased risk. To assess the sensitivity of the results for changes in particular emission factors, measured data from NC-grass field experiments was applied. Comparisons were as follows:

**1) N<sub>2</sub>O emissions from fertilisers and crop residues (mineral soils)**

- Regina et al. (2013) calculation method, based on empirical data from Finland (Note: this method is used in the baseline scenario in EnreBeef).
- IPCC (2006) emission factors (EFs) and lower and upper EFs within the uncertainty range
- NC-grass Eddy Covariance measurements – Anttila

**2) N<sub>2</sub>O emissions from drained organic soils**

- IPCC (2014) EFs (boreal grassland) and lower and upper EFs within the uncertainty range
- NC-grass Eddy Covariance measurements – Pappilansuo and Särkisuo

The majority of GHG emissions in the beef production (baseline scenario) chain were related to enteric methane, followed by feed cultivation (**Table 14**). The GHG emissions related to feed cultivation were higher in the East than in South Finland due to the higher share of organic soil, causing CO<sub>2</sub> and N<sub>2</sub>O emissions. Eutrophication was mainly caused by N and P leaching and runoff in feed cultivation. Acidification potential was related mainly to manure management and manure application on grass.

**Table 14.** Shares of different emission sources out of total environmental impact, separately for East and South Finland (baseline scenario).

		Climate impact		Eutrophication		Acidification	
		East	South	East	South	East	South
Barley	cultivation emissions	26 %	19 %	35 %	35 %	9 %	10 %
Silage grass	cultivation emissions	21 %	16 %	55 %	54 %	46 %	45 %
Enteric methane		39 %	48 %	-	-	-	-
Manure	management emissions	10 %	12 %	10 %	11 %	42 %	41 %
Animal housing emissions		4 %	5 %	1 %	1 %	3 %	3 %

Out of the eight management method scenarios modelled, especially increased yield on mineral soils (and exclusion of organic soils, scenario 2), cover cropping (scenario 3), and increased yield rates (scenarios 6 and 7) showed potential to reduce the environmental impact of beef (**Table 15**). The effect of cover cropping is related mainly to promoted soil carbon sequestration, yet it is accounted for in LCA only for a fixed time (here: 20 years). After that period, cover cropping is not assumed to increase the soil carbon stock anymore. Increased yield rates have the potential for improved environmental efficiency, although the potential is limited by biotic and abiotic factors as well as socio-economic factors.

Increased grass cut height (scenario 1) showed conflicting results. Although climate impact decreased somewhat following increased carbon input to soil, eutrophication potential increased due to lower grass yields and thus, increased requirement of field area per animal (**Table 15**). Increased water table level (scenario 4) efficiently cut the GWP of feed production on organic soils, but the effect was diluted when all GHG emissions sources throughout animal life were considered. In total, the GWP of beef decreased by 3–8 % following water table management. Following an increase in the silage-to-concentrate ratio, increased environmental impact was observed (**Table 15**), similar to previous research (Huuskonen et al., 2023). The underlying reason for this relates to reduced animal growth and decreased feed conversion.

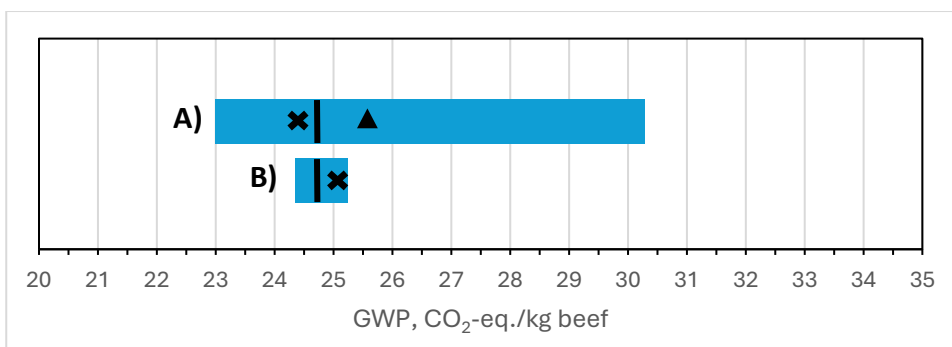
**Table 15.** Change in the environmental risks due to change in management methods, compared with the baseline scenario.

Scenario	Climate impact	Eutrophication	Acidification
----------	----------------	----------------	---------------

East Finland	1) Increased grass cut height	-	+	
	2) Increased yield on mineral soils	---	--	
	3) Cover crops added for barley	--	-	
	4) Increased water table level	-		
	5) Organic soil fields used for grasses only			
	6) Increased yield, high		--	--
	7) Increased yield, very high	--	---	---
	8) Increased silage to concentrate ratio	+	++	+++
South Finland	1) Increased grass cut height	-	+	
	2) Increased yield on mineral soils	--	-	
	3) Cover crops added for barley	--	-	
	4) Increased water table level			
	5) Organic soil fields used for grasses only			
	6) Increased yield, high	-	---	---
	7) Increased yield, very high	--	---	---
	8) Increased silage to concentrate ratio	+	+	+++

Yellow = neutral risk, green = decreased risk, red = increased risk. Number of +/- marks indicates the magnitude of risk change: + = +5–10 % compared with baseline; ++ = +10–20 %; +++ = >20 % on correspondingly for minus marks.

NC-grass Eddy-Covariance measurements provided N<sub>2</sub>O EFs relatively similar with IPCC (2006, 2014) EFs and somewhat lower compared with Regina et al. (2013) as illustrated in **Fig. 2**. When the effect of different N<sub>2</sub>O estimates was compared per 1 kg of beef, the results based on NC-grass measurements differed by -2 % to +1 % from results based on IPCC EFs. From the results calculated with the Regina et al. (2013) method, the difference was -12 %.



**Figure 25.** Sensitivity of the results for emission factors (EF): **A)** N<sub>2</sub>O from fertilisers and crop residues – IPCC (2006) emission factors vs. NC-grass measurement data (Anttila), **B)** N<sub>2</sub>O from drained organic soils – IPCC (2014) emission factors vs. NC-grass measurement data (Pappilansuo, Särkisuo). **Purple horizontal bars** = range of GWP within the uncertainty range of IPCC N<sub>2</sub>O EFs, **black vertical line** = GWP calculated with IPCC N<sub>2</sub>O EFs, **black cross** = GWP calculated with NC-grass field experiment data, black triangle = GWP calculated with Regina et al. (2013) method.

Out of studied management methods, cover cropping on barley and intensified cultivation on mineral soil fields while excluding organic soil fields showed potential to reduce the life-cycle environmental impact of beef production. Also, water table management on organic soil and increased grass cut height showed slight potential. The NC-grass measurement data showed to provide estimates relatively similar to widely used LCA emission factors.

**MACC analysis and Enviro – Economic analysis:** This analysis was planned in the project earlier by Galyna Medyna. However, these plans had to be dropped in view of her demise during the project period. Nevertheless, her colleagues (**Pooja Yadav**) has started to work on this aspect. However, this work needs to be developed further.

### **Social sustainability (Luke - Tiina Mattila, Olli Niskanen and Annina Lehtilä)**

Social sustainability was described on the sector level using a few key indicators. These were age distribution of the farmers, income level, and occupational health and safety. The choice of indicators was based on the UN Sustainable Development Goals and the framework of the Finnish food chain derived from these by Yli-Viikari and Reinikainen (2022). Group interview was used to assess the health and safety risks in the grass production on farm level. For this purpose and as a basis for discussion the grass production process of a fictitious farm was described with the following specifications: location in Pohjois-Savo, conventional farming, combined milk and meat production, 4-year grassland, farm size 86 ha (partly peatland) and 67 animal units, farm net income 40 000 e, profitability ratio 0,5, family farm (farmer, spouse, and one teenage child), one hired seasonal worker. The risks were first assessed and discussed at baseline situation and then the impact of the possible changes in cultivation, such as timing of tillage (autumn vs. spring), changes in grass cutting height, changing the groundwater levels in fields, using organic fertilizers instead of mineral fertilizers, and legume cropping. The participants of the group interview were selected to cover expertise on injury risks, hazardous work exposures, musculoskeletal and mental strain of the farm work, farm economy, and grass production.

#### Age of the farmers and number of farms

The farming population is ageing; an average age of the Finnish farmers was 54 years in 2022 (Luke statistics, 2023). Dairy and beef producers are a bit younger than all farmers on average (Figure 26). Only around 14% of all farmers were under 40 years old in 2022; retired farmers (65+ years) owned 20% of farms and 11% of farmland (Jaakkonen & Väre, 2023). Young people's interest in the sector is low and an assessment is that in ten years, one third of farms in Finland is owned by retired farmers (Jaakkonen & Väre, 2023). The same phenomenon can be seen across the Europe - in the EU, 58% of primary farmers were over 54 years of age in 2020 (Eurostat, 2023).

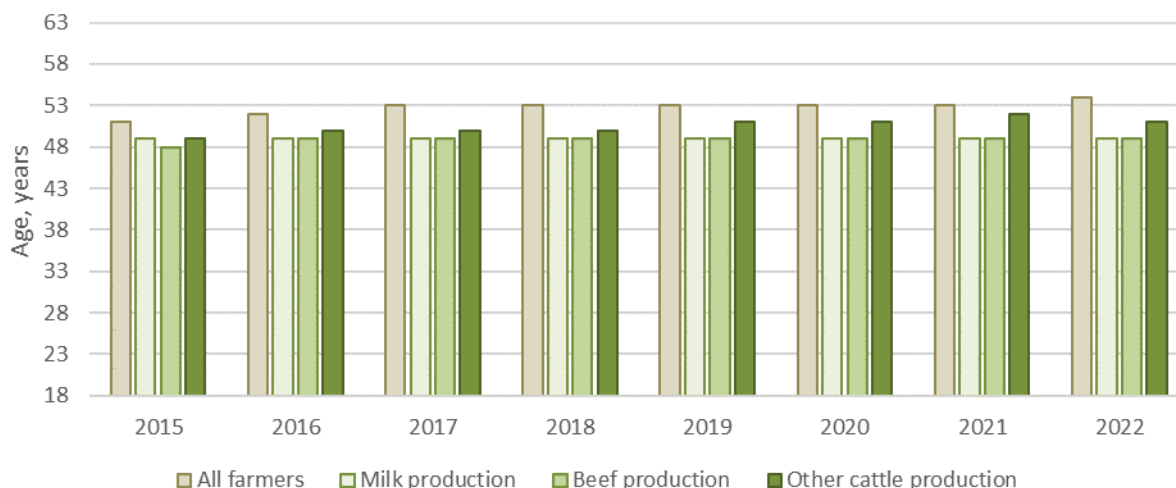


Figure 26. An average age of Finnish farmers in years 2015 – 2022 (Luke statistics, 2023).

The annual number of generation switches and new agricultural entrepreneurs is not enough to maintain the number of farms. While there were 43,540 agricultural and horticultural companies in operation in 2022 (Luke statistics, 2023), in 2027 there will be approximately 32,800 farms, according to a forecast based on an extensive survey produced by Kantar TNS Agri Ltd. (2023), and the figure for 2030 will be 28,500. When the total arable area remains almost unchanged, the average farm size will rise to 80 hectares at the turn of the next decade.

In 2030, there will be around 7,000 farms of more than 100 ha, and they already have more than half of the arable land. There are about 2,000 farms over 200 hectares, and these have a good quarter of the arable area. However, there are still around 6,000 farms of less than 20 ha.

The structural development that has been going on for a long time is strongest in livestock production. According to the estimate of Kantar, the number of dairy farms will be halved in ten years in accordance with the realized trend, and at the end of the decade there will be approximately 2,250 dairy farms. The development will lead to a decrease in the number of cows, as there are fewer new enlarging investments at the continuing farms expected to replace the cow places that are being removed. The development is rather similar at other cattle farms, from the 2960 farms active in 2022, approximately 2000 would continue until 2030 (Kanter TNS Ltd., 2023).

#### Income level on dairy and other cattle farms

Profitability and wage levels on dairy and other cattle farms have been rather modest on average (Table 16). Measured by profitability ratio<sup>1</sup>, farmers have gained on average less than half from their cost claim for family working hours and interest demand for their own capital. Hourly earnings for the own labor input have varied between 4,8 and 9,6 euro per hour in dairy production and 4,4 and 8,2 euro per hour in other cattle farms. In absolute terms, family farm income has varied between 24 700 and 50 400 euros per year in dairy production and 15 400 and 32000 per farm (Table 16). Dairy and other cattle farming are typically full-time jobs that limits the opportunities for getting other incomes (salary work or other business)

Table 16. Average Financial Ratios of the Finnish dairy and other cattle farms in years 2012 – 2021 (Resource: Luke Economydoctor, 2023).

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
<b>Farm net income<sup>a</sup></b>										
Dairy	47 000	39 700	47 400	30 800	24 700	35 200	28 800	36 300	47 200	50 400
Other cattle	24 400	32 000	24 000	26 100	15 400	28 400	23 100	28 200	27 600	30 000
<b>Profitability Ratio<sup>b</sup></b>										
Dairy	0,59	0,52	0,6	0,38	0,3	0,45	0,35	0,45	0,57	0,6
Other cattle	0,41	0,55	0,44	0,48	0,28	0,52	0,39	0,45	0,48	0,51
<b>Return on hour of family work<sup>c</sup></b>										
Dairy	8,6	7,7	9,1	6	4,8	7,1	5,7	7,2	9,2	9,6
Other cattle	5,9	8,2	6,6	7,6	4,4	8,1	6,3	7,3	7,7	8,2
<b>Equity Ratio<sup>ed</sup></b>										
Dairy	70,6	69,1	67,6	64,3	63	62,9	62,7	62,9	60,6	63,5
Other cattle	67,9	69,7	67,1	67,3	65,1	59,7	63,2	63	62,6	67,3

<sup>a</sup>Farm net income = Gross Return - costs without wages claim

<sup>b</sup>Profitability Ratio = Family farm income / (wages claim + interest claim)

<sup>c</sup>Return on hour of family work (€/h) = Profitability ratio \* wages claim per hour

<sup>d</sup>Equity Ratio = 100 \* Equity / total capital

## Occupational health and safety

Injury rate of the Finnish farmers has been decreasing in the long run (Figure 2). However, during the last twelve years the trend has tended to turn upwards. The main reason behind the unwanted change in the trend in recent years was the termination of the premium discount system (no-claims bonus) of the mandatory accident insurance (Mata) in the end of 2015 (Karttunen and Rautiainen, 2021). Especially injury claims with 0 compensated disability days increased (Karttunen and Rautiainen, 2021). Overall, Finland has a comprehensive accident insurance system and therefore statistics do not suffer from the same kind of serious under-reporting problems as many other countries' i.e. statistics give a reliable picture of the situation (Karttunen & Rautiainen, 2013; Merisalu et al., 2019; Jacob et al., 2021).

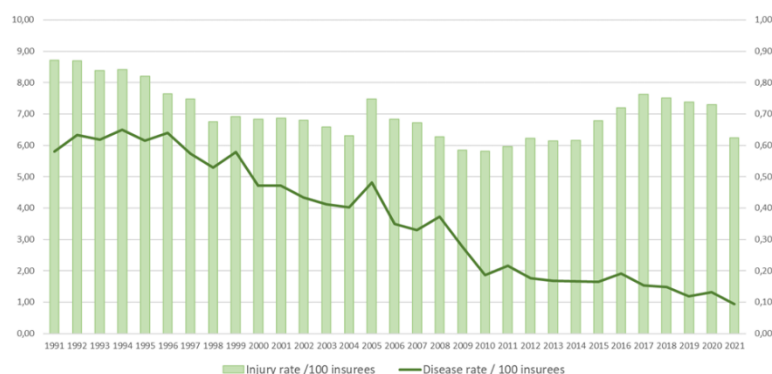


Figure 27. Farmers' injury rate in years 1991 – 2021. Resource: Mela Statistics, 2023.

Risk factors for injuries in agriculture in general are quite well known. Jadhav et al. (2015) and Jadhav et al. (2016) found in their meta-analysis several risk factors for agricultural injuries. Part of these were factors related to the strategic choices and job profile of a farmer, like full-time farming, owner/operator status (vs. family member or hired worker), farm size, and livestock production. Quite many of risk factors were related to the farmers' occupational health like regular medication use, stress or depression, hearing loss, and sleep disturbances. The analysis by Jadhav et al. (2016) also highlights challenging social circumstances as a risk factor; financial difficulties or problems with social relationships can make it difficult to maintain the safety on the farm.

Karttunen (2014) noticed in his doctoral thesis that aging livestock farmers are a particular risk group both for occupational injuries, diseases, and disability. Livestock production and particularly physical contact with cattle exposes farmers to injuries. Also repair and maintenance of farm machinery is a particularly risky work phase (Karttunen, 2014). Overall, the share of machinery-related injuries appears to have slightly increased over years (Mela Statistics, 2023).

Even though technology has developed and working conditions improved in many farms, there are still a wide range of smaller farms with outdated and undeveloped working conditions which may expose farmers for injuries and other health problems. In addition, despite of modernization, the larger farms have neither been able to manage occupational health and safety risks in an optimal way and e.g., musculoskeletal problems are a serious problem (Osborne 2012a; Osborne 2012b; Karttunen, 2014). Compared to the typical causes of disability pensions in Finland in general, among farmers the musculoskeletal diseases and injuries are more frequent, and mental disorders less frequent than in the whole population (Karttunen et al., 2015; ETK, 2023). Difficult working postures, heavy lifting and carrying, inadequate recovery, constant hurry, and economic uncertainty as well as older age and female gender are risk factors for musculoskeletal symptoms (Mattila et al., 2021). In plant production, vibration, prolonged vigilance, and long tractor-driving hours increase the risk (Fathallah, 2010; Hartman et al., 2006).

Occupational diseases are illnesses that are likely to be caused mainly by a physical, chemical, or biological agent at work and are compensable as occupational diseases under occupational disease legislation. All work-related diseases are not classified as occupational diseases. Among Finnish farmers, the occupational disease rate has a downward trend (Figure 27) (Mela, statistics 2023), but agriculture remains a high-risk sector for occupational asthma, occupational rhinitis, contact urticaria or protein contact dermatitis, lateral epicondylitis (tennis elbow) and noise-induced hearing loss (TTL, 2022). Also, mole fever and cryptosporidiosis are typical for farmers. Ammonia and hydrogen sulfide originating from animal sludge is a health and safety risk for farmers and may cause asthma (Lindström et al., 2021), meaning that exposure risk should be carefully analyzed and inspected concerning all the sludge handling maneuvers.

### **3.6 WP6 – Communication and dissemination (Valio, Yara and Atria)**

Valio is developing farm-level life cycle calculation (Carbo® Farm Calculator) for raw milk and beef production in Finland. Field block-specific modeling of the climate effects of cultivation is the next development step. Valio also trains dairy farms in regenerative farming, which increases carbon sequestration in the arable land and reduces farming's greenhouse gas emissions. Efforts have been made to utilize the results of the NC-GRASS project, for example, in the development projects mentioned above. As a part of the scientific communication from the project, the number of papers published during the project period are listed separately in the next section.

#### **Conferences**

Accurate simulation of greenhouse gas emissions across fertilizer scenarios with DNDC, T Thentu, D Forster, P Virkajärvi, MT Harrison, N Shurpali EGU General Assembly Conference Abstracts, 7642, 2024

Impact of management and boreal climate on GHG exchange from Finnish grasslands on mineral and peat soils, N Shurpali, O Peltola, T Thentu, P Virkajärvi, EGU24

Current research view about nitrous oxide uptake in agricultural soils, HR Bhattarai, et al., Grassland at the heart of circular and sustainable food systems, 104 European Grassland federation (EGF2022) in Caen France—ENSINK (poster)

Modelling studies of beef and dairy farming in boreal environments: a review., D Forster, S Helama, P Virkajarvi, NJ Shurpali, Grassland at the heart of circular and sustainable food systems,

Evaluating GHG simulation performance of DNDC in a boreal grassland setting, D Forster, J Deng, MT Harrison, NJ Shurpali, International Symposium on Climate-Resilient Agri-Environmental Systems, ISCRAES, Dublin, August 2022

International Symposium on Climate-Resilient Agri-Environmental Systems (ISCRAES 2022) Dublin, Ireland—ENSINK (a talk) Title: “The role of red clover—a forage legume, in mitigating nitrous oxide (N<sub>2</sub>O) emissions from a perennial grassland”

Carbo Science Seminar , Helsinki, Finland 25.10.2022, Narasinha Shurpali (a talk)

#### **4. Publications and manuscripts produced by the project**

Fer I, Bell Q, Kajasilta H, Nevalainen O, Höckerstedt L, Varjonen S, Tang H, Vira J, Kulmala L, Liski J: manuscript preliminary entitled 'A retrospective analysis of seasonal agricultural forecasts to improve carbon sequestration and decision support at Field Observatory Network (FiON) sites' to be submitted for review late 2024.

Forster, Daniel, Jia Deng, Matthew Tom Harrison, and Narasinha Shurpali. 2022b. “Simulating Soil-Plant-Climate Interactions and Greenhouse Gas Exchange in Boreal Grasslands Using the DNDC Model.” *Land* 11 (11): 1947. <https://doi.org/10.3390/land11111947>

Forster, Daniel, Samuli Helama, Matthew T. Harrison, Clarence Alan Rotz, Jinfeng Chang, Phillippe Ciais, Elizabeth Pattey, Perttu Virkajärvi, and Narasinha Shurpali. 2022a. “Use, Calibration and Verification of Agroecological Models for Boreal Environments: A Review.” *Grassland Research* 1 (1): 14–30. <https://doi.org/10.1002/glr2.12010>

Gerin Stephanie, Henriikka Vekuri, Maarit Liimatainen, Juha-Pekka Tuovinen, Jarkko Kekkonen, Liisa Kulmala, Tuomas Laurila, Maiju Linkosalmi, Jari Liski, Erkki Joki-Tokola, Annalea Lohila (2023): Two contrasting years of continuous N<sub>2</sub>O and CO<sub>2</sub> fluxes on a shallow-peated drained agricultural boreal peatland, *Agricultural and Forest Meteorology*, <https://doi.org/10.1016/j.agrformet.2023.109630>

Heimsch Laura, Julius Vira, Istem Fer, Henriikka Vekuri, Juha-Pekka Tuovinen, Annalea Lohila, Jari Liski, Liisa Kulmala, a manuscript entitled ‘*Impact of Weather and Management Practices on Greenhouse Gas Flux Dynamics on an Agricultural Grassland in Southern Finland*’ submitted manuscript AGEE in Feb 2024, in review

Kajasilta H, Fer I, Kulmala L, Läpikivi M, Liimatainen M, Liski J, Niiranen M, and Vira J: manuscript preliminary entitled '*The impact of peat and water table depth on GHG fluxes on northern agricultural shallow peatlands*' to be submitted for review late 2024.

Oliveira, R. A., Näsi, R., Korhonen, P., Mustonen, A., Niemeläinen, O., Koivumäki, N., ... & Honkavaara, E. (2024). High-precision estimation of grass quality and quantity using UAS-based VNIR and SWIR hyperspectral cameras and machine learning. *Precision Agriculture*, 25(1), 186-220. <https://doi.org/10.1007/s11119-023-10064-2>.

Oliveira, R. A., Näsi, R., Korhonen, P., Mustonen, A., Niemeläinen, O., Koivumäki, N., ... & Honkavaara, E. (2023). Hyperspectral UAS imagery for grass swards biomass and nitrogen estimation. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 48, 1861-1866.

Näsi, Korhonen, Kivimäki, Oliveira, Peltola, Puttonen, Kaivosoja, Mylly, Honkavaara, Shurpali. Quantifying Greenhouse Gas Emission Potential from Organic Soils in Finnish Grass Production: A Satellite-Based Assessment of Cultivation Intensity (Manuscript under preparation)

Tulasi Thentu et al Modelling of GHG exchange from a Boreal legume grassland region using DNDC model under organic and inorganic managements (to be submitted in 2024)

Forster et al., Forecasting Increased Soil Carbon Storage Under Future Climate Scenarios in Boreal Grasslands (to be submitted in 2024)

Shurpali et al., Field-scale greenhouse gas fluxes at three managed boreal grasslands (to be submitted in 2024)

## **5. Evaluation of the implementation phase and results**

### **5.1. Practical applicability of the results**

#### **What are the practical implications/meaning of the results?**

- Uncalibrated Basgra and L-DNDC simulate the seasonal dynamics of NEE well in mineral soils (Viikki), but underestimate the increased respiration in spring before the actual growing season and the increase in photosynthetic uptake. In Viikki, STICS was also able to simulate the spring period sufficiently. The performance of L-DNDC on peat soil (Ruukki) and HE-DNDC on mineral soil (Anttila) would still benefit from calibration. Even if the seasonal dynamics are fine, short-term under- or overestimation of events can lead to significant differences in the annual balances.
- The management data is an important input not only as a model input but also because the input and output by the farmer contribute significantly to the C balance. The availability of management data is necessary on a landscape or regional level and therefore national efforts for data handling are needed.

#### **Are the results useful, e.g. for the development of new farming methods or food processing, product development or marketing?**

- These results serve as a baseline whereas more data is still needed to quantify the impact of new farming methods. However, these observations and simulations can be used when calculating the carbon footprint of the studied farming practices.

### **Is there potential for patenting?**

- NA

### **How do the results help public authorities in their regulatory work?**

- NC GRASS offered a robust foundation for developing and refining strategies to meet carbon reduction targets by increasing the amount of data available and models able to simulate agricultural carbon sequestration in Finland.
- The progress in agroecosystem modelling allowed evaluating the environmental impact of different agricultural practices. This is similar to how California State uses advanced models for regulatory and policy decisions in managing carbon sequestration and GHG emissions.
- NC GRASS emphasizes the importance of holistic data management systems drawing parallels with initiatives like PEcAn, which integrates ecosystem data and models to inform decision-making. Such systems ensure that comprehensive and accessible data supports regulatory frameworks and environmental monitoring.
- The contributions can be aligned with standards and verification processes used by organizations like VERRA, which develops and manages standards for climate action and sustainable development. By providing reliable data and validated models, the project supports the development of verified carbon standards and methodologies, aiding regulatory compliance and environmental accountability.

### **Do the results contribute to the creation of new business?**

- The testing and development of ecosystem models potentially contribute to the creation of new business in MRV front for example by estimating carbon sequestration for carbon farming certificates.

### **Who could be the beneficiaries of the results?**

- Potential beneficiaries are for example 1) verification system developers and users such as the food industry, national greenhouse gas inventory, and carbon farming certificate providers, 2) climate scientists improving their estimates for the climatic impact of Finnish agriculture

### **Have the results already been exploited, if so, where and how?**

- The results have been so far mainly used in scientific development and manuscripts/articles building a baseline for the climatic impact of Finnish agricultural fields and developing monitoring methods for agricultural carbon sequestration.

### **How and where will the results be used in the future?**

- The results will be utilized in the development and application of MRV systems which can be applied to different contexts such as national inventories, carbon farming certificates, life cycle analyses etc.
- These results set the baseline for GHG exchange in Finnish agriculture and can be used for example in studying the role of different weather and agricultural drivers and how to handle and manage those in suitable way also in changing future climate.

## **5.2 The scientific significance of the results**

### **What is the added value of the results compared to the previous (scientific) knowledge base?**

**Enhanced Data Collection on Agricultural Carbon Sequestration:** Evaluating the potential of agriculture to sequester atmospheric carbon necessitates detailed local observations of various farming practices. This project has substantially increased the volume of such data in Finland, providing a more comprehensive understanding of how different agricultural methods can contribute to carbon sequestration.

**Advancement in Agroecosystem Modelling:** Before this project, Finland had limited activities and expertise in agroecosystem modelling, particularly concerning carbon and nitrogen cycles. The previous modelling efforts by LUKE predominantly focused on yield. This project has significantly enhanced the expertise in Finland and facilitated advanced model testing and evaluation of C and N cycles within agroecosystems. As a result, the project has not only broadened the scope of agroecosystem modelling in Finland but also strengthened the scientific community's ability to address these critical environmental issues.

**Long-term Data on Annual Carbon Variation:** In the manuscript by Heimsch et al., we evaluated the year-to-year variation in carbon sequestration and carbon balance. We are generating continuous GHG flux data from several research sites, which was not the case earlier. Such long data sets are rare, and reporting the annual variation provides valuable insights into the impact of different weather conditions on carbon dynamics. This long-term perspective is crucial for understanding the resilience and response of agricultural systems to climatic variability.

### **What is the value of the results internationally?**

Having more data and tested agricultural models from Nordic countries enriches the global dataset and offers insights into carbon dynamics in cooler climates and contributing to more accurate global models of carbon sequestration. An understanding of what modelling aspects are properly represented in simulations and what is not is a powerful tool in building more robust models capable of realistic representations of ecosystems under investigation.

### **What theses were produced because of the NC-GRASS research?**

Petra Manninen, is pursuing here PhD as a part of the AKA funded ENSINK project. Her PhD thesis has relevance to the NC-GRASS project results.

Ville Nieminen, has completed his MS thesis from the University of Jyväskylä in 2024 and th results from his thesis have relevance to this project.

Pitkänen, J., 2023. Estimating biomass of silage grass production parcels using an uncrewed aerial system and satellite remote sensing. Aalto yliopisto. Master's thesis.  
<https://urn.fi/URN:NBN:fi:aalto-202305283432>

### **How should further research or projects be targeted and prioritised?**

Future research should prioritize the development and implementation of comprehensive data management systems. Ensuring that data is easily accessible and well-organized will facilitate more effective analysis and sharing among researchers, ultimately enhancing the quality and impact of scientific findings.

Encouraging the sharing of modelling results between different research institutions is essential. This collaboration will help synthesize results from various models which provides a more robust and unified understanding of agroecosystem processes as single models tend to result in biases. Such an approach will also promote the validation and improvement of models through cross-comparison and collective insights.

There should be a strong focus on advancing the modelling of organic soils and their interaction with water management practices. Understanding these dynamics is crucial for developing sustainable agricultural practices that optimize carbon sequestration and minimize environmental impacts.

Further research must prioritize the study of nitrous oxide (N<sub>2</sub>O) dynamics, leaching losses, and ammonia emissions. These factors are critical components of the nitrogen cycle and have significant implications for both greenhouse gas emissions and nutrient management in agricultural systems. Addressing these issues together with carbon sequestration will contribute to more sustainable and environmentally friendly farming practices.

Current grassland models have some deficiencies.

To increase the biodiversity, grasslands are no longer monocultures, they are mixed grassland systems. Current models do not account for more than one species being cultivated at a site. Models need to describe different vegetation types and their interactions among different vegetation types.

There is a dearth of models for agricultural peat soils.

UAS-based data were shown to be a promising tool for grass parameter estimation. Particularly multispectral and hyperspectral UAS datasets showed consistent performance for yield quality and quantity estimation. However, the methodology still needs to be developed to generalize the models to build robust tools for practical applications. A significant limitation of the Sentinel datasets is the limited availability of cloud-free images, which can restrict their usability for time-critical applications. However, for non-time-critical applications, they offer a low-cost approach for crop estimations. The increasing amount of reference data for satellite-based models enables the development of accurate estimation methods across Finland and globally, utilizing freely available Sentinel-2 data. This would enhance the performance of silage production, addressing the challenges of climate change mitigation and the needs of a growing population.

Remote sensing data can be used to evaluate cultivation intensity of organic (Dystric and Sapric Histosols) field parcels used for grass production by assessing number of annual harvest events as observed from changes in vegetation indices in Finnish grass production regions. The frequency of harvest events is linked to the presence of excess water, hindering efficient production on the parcels and concurrently influencing GHG emission patterns emanating from the fields.

## Challenges

WP1 and WP2: One of the major tasks in the project was to compile a database from published literature on agricultural management practices and their associated GHG fluxes. This proved to be a challenging task as the scientific literature globally is not consistent in reporting the data needed for a thorough meta-analysis.

WP 3: Minor adjustments were made to the objectives based on the available datasets and research questions that emerged during the project. In WP 3.2, the Cybergrass I datasets were utilized in the

NC-Grass project, providing easy access to a significant number of field parcels. Instead of focusing on N-fertilization, yield estimation was made the primary objective, serving as a proxy for carbon sequestration in grass fields. In WP 3.4, it was decided to perform satellite image-based analysis of harvesting activities and subsequently test the hypothesis regarding the relationship between water management, productivity, and carbon emissions.

WP4 Planned Integrated farming systems modelling (IFSM) did not fit the purpose but that was noticed in the initial phase and the resources could be allocated to testing and developing the field-scale ecosystem models.

There is not a higher education with courses on ecosystem modelling which would train for the purpose. Therefore, there is a lack of skilful people in Finland and recruiting one for LUKE for the project was challenging causing extra delays in addition to the learning curve. We recommend for establishing a training for modelling skills as such expertise needs do exist in Finland.

WP5 Planned MACC analysis could not be carried out owing to situations not in anyone's control (untimely demise of Galyna Medyna during the project time). Resources and time were of constraint to carry out a detailed social risk analysis and therefore, a brief review of the work done in Finland was performed.

## **Presentations**

Eija Honkavaara, 14.-15.6.2022. Nurmen määrän ja laadun estimointi droonikaukokartoituksella. Maataloustieteen päivät.

Roope Näsi , 10.11.2022 . How drones can be utilized in milk production? FGI Research Seminar

Raquel Oliveira, 16.2.2023. Performance evaluation of novel UAS-based VNIR and SWIR hyperspectral imaging for grass quality and quantity estimation, FinDrones 2023 -seminar

Roope Näsi, 16.2.2023. Remote sensing methods for evaluating the properties related to the production capacity of field parcels, FinDrones 2023 -seminar

Raquel Oliveira, 15.4.2023, hyperspectral UAS imagery for grass swards biomass and nitrogen estimation, The ISPRS Geospatial Week - Egypt GSW'2023.

Shurpali et al., EGF 2024, Leeuwarden

Bhattarai et al., EGF 2024, Leeuwarden

Shurpali et al., ISCRAES, Dublin 2024

Shurpali NJ et al., EGF 2023 – Vilnius, Latvia

Bhattarai et al., EGF 2023 – Vilnius, Latvia

Bhattarai et al, COP27, Egypt 2022

Accurate simulation of greenhouse gas emissions across fertilizer scenarios with DNDC, T Thentu, D Forster, P Virkajärvi, MT Harrison, N Shurpali, EGU General Assembly Conference Abstracts, 7642 2024

Impact of management and boreal climate on GHG exchange from Finnish grasslands on mineral and peat soils N Shurpali, O Peltola, T Thentu, P Virkajärvi, EGU24

## Literature cited

2006 IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use. Chapter 5: Cropland. 309–317.

Beaudoin N., Lecharpentier P., Ripoche D., Strullu L., Mary B., Leonard J., et al. (Eds.), (2022) STICS Soil-Crop Model. Conceptual Framework, Equations and Uses, Versailles, Éditions Quæ, 519 pages, <https://library.oapen.org/handle/20.500.12657/85111>

Brisson N., Gary C., Justes E., Roche R., Mary B., Ripoche D., Zimmer D., Sierra J., Bertuzzi P., Burger P., Bussière F., Cabidoche Y. M., Cellier P., Debaeke P., Gaudillère J. P., Hénault C., Maraux F., Seguin B., Sinoquet H. (2003) An overview of the crop model STICS. *Europ J Agro* 18(3-4):309–332. [https://doi.org/10.1016/S1161-0301\(02\)00110-7](https://doi.org/10.1016/S1161-0301(02)00110-7)

Burdun, Iuliia & Bechtold, Michel & Sagris, Valentina & Lohila, Annalea & Humphreys, Elyn & Desai, Ankur & Nilsson, Mats & De Lannoy, Gabriëlle & Mander, Ülo. (2020). Satellite Determination of Peatland Water Table Temporal Dynamics by Localizing Representative Pixels of A SWIR-Based Moisture Index. *Remote Sensing*. 12. 2936. 10.3390/rs12182936.

Deng, J.; Li, C.; Frohling, S.; Zhang, Y.; Bäckstrand, K.; Crill, P. Assessing effects of permafrost thaw on C fluxes based on multiyear modeling across a permafrost thaw gradient at Stordalen, Sweden. *Biogeosciences* **2014**, 11, 4753–4770.

Deng, J.; Xiao, J.; Ouimette, A.; Zhang, Y.; Sanders-DeMott, R.; Frohling, S.; Li, C. Improving a Biogeochemical Model to Simulate Surface Energy, Greenhouse Gas Fluxes, and Radiative Forcing for Different Land Use Types in Northeastern United States. *Glob. Biogeochem. Cycles* **2020**, 34, e2019GB006520.

Earth Resources Technology Satellite Symposium, Greenbelt 10-14 December. SP-351:

Forster, Daniel, Jia Deng, Matthew Tom Harrison, and Narasinha Shurpali. 2022b. “Simulating Soil-Plant-Climate Interactions and Greenhouse Gas Exchange in Boreal Grasslands Using the DNDC Model.” *Land* 11 (11): 1947. <https://doi.org/10.3390/land11111947>.

Gao, B. 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, 58, 3, 257–266. [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3).

Gerin S, Vekuri H, Liimatainen M, Tuovinen JP, Kekkonen J, Kulmala L, Laurila T, Linkosalmi M, Liski J, Joki-Tokola E, Lohila A (2023) Two contrasting years of continuous NO and CO fluxes on a shallow-peated drained agricultural boreal peatland. *Agricultural and Forest Meteorology* 341, 109630, <https://doi.org/10.1016/j.agrformet.2023.109630>

Giltrap, D.L., Li, C., Sagar, S., 2010. DNDC: A process-based model of greenhouse gas fluxes from agricultural soils. *Agric. Ecosyst. Environ.* 136 (3–4), 292–300. <https://doi.org/10.1016/j.agee.2009.06.014>.

Gould, R., Ilmarinen, J., Järvisalo, J., & Koskinen, S. (Eds.). (2008). *Dimensions of Work Ability, Results of the Health 2000 Survey*. Helsinki: Finnish Centre for Pensions, The Social Insurance Institution, National Public Health Institute, Finnish Institute of Occupational Health.

Haas E., Klatt S., Fröhlich A., Kraft P., Werner C., Kiese R., Grote R., Breuer L. and Butterbach-Bahl K. (2013) LandscapeDNDC: a process model for simulation of biosphere–atmosphere–hydrosphere exchange processes at site and regional scale. *Landscape ecology*, 28, pp.615-636. <https://doi.org/10.1007/s10980-012-9772-x>

Heimsch L, Lohila A, Tuovinen J-P, Vekuri H, Heinonsalo J, Nevalainen O, Korkiakoski M, Liski J, Laurila T, and Kulmala L (2021): Carbon dioxide fluxes and carbon balance of an agricultural grassland in southern Finland. *Biogeosciences* 18, 3467–3483. <https://doi.org/10.5194/bg-18-3467-2021>

Heimsch L, Vira J, Fer I, Vekuri H, Tuovinen J-P, Lohila A, Liski J, Kulmala L (2024), Impact of Weather and Management Practices on Greenhouse Gas Flux Dynamics on an Agricultural Grassland in Southern Finland, submitted to Agriculture, Ecosystem and Environment (in review)

Höglind, M., Cameron, D., Persson, T., Huang, X., Van Oijen, M., (2020). BASGRA\_N: A model for grassland productivity, quality and greenhouse gas balance. Ecological Modelling 417. <https://doi.org/10.1016/j.ecolmodel.2019.108925>

Höglind, M., Van Oijen, M., Cameron, D., Persson, T., (2016). Process-based simulation of growth and overwintering of grassland using the BASGRA model. Ecological Modelling 335, 1–15. <https://doi.org/10.1016/j.ecolmodel.2016.04.024>

<https://doi.org/10.1109/JSTARS.2019.2938388>

<https://portal.mtt.fi/portal/page/portal/taloustohtori>. Accessed 15.10.2023

<https://unfccc.int/documents/627718>

[https://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4\\_Volume4/V4\\_05\\_Ch5\\_Cropland.pdf](https://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_05_Ch5_Cropland.pdf)

[https://www.ipcc-](https://www.ipcc-nggip.iges.or.jp/public/wetlands/pdf/Wetlands_separate_files/WS_Ch2_Drained_Inland_Organic_Soils.pdf)

[nggip.iges.or.jp/public/wetlands/pdf/Wetlands\\_separate\\_files/WS\\_Ch2\\_Drained\\_Inland\\_Organic\\_Soils.pdf](https://www.ipcc-nggip.iges.or.jp/public/wetlands/pdf/Wetlands_separate_files/WS_Ch2_Drained_Inland_Organic_Soils.pdf)<https://link.springer.com/article/10.1007/s11027-014-9559-2>

<https://www.sciencedirect.com/science/article/pii/S1871141323000136>

IPCC 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands. Chapter 2: Drained Inland Organic Soils.

Jadhav, R., Achutan, C., Haynatzki, G., Rajaram, S., & Rautiainen, R. 2015. Risk factors for agricultural injury: A systematic review and meta-analysis. Journal of Agromedicine, 20(4), 434-449. doi:10.1080/1059924X.2015.1075450

Jadhav, R., Lander, L., Achutan, C., Haynatzki, G., Rajaram, S., Patel, K., & Rautiainen, R. 2016. Review and meta-analysis of emerging risk factors for agricultural injury. Journal of Agromedicine, 21(3), 1-14. doi:10.1080/1059924X.2016.1179611

Jakob, M.C., Santa, D., Holte, K.A., Sikkeland, I.J., Hilt, B., Lundqvist, P. 2021. Occupational Health and Safety in Agriculture – a brief report on organization, legislation, and support in selected European countries. Annals of Agricultural and Environmental Medicine 28(4): 452–457. doi: 10.26444/aaem/140197

Karttunen, J. 2014. Clustering of occupational injuries, diseases, and disability in Finnish farmers – an opportunity for targeted prevention. Doctoral Thesis in Agrotechnology. Department of agricultural sciences. Publications 23. University of Helsinki. 65 s.

Karttunen, J.P. & Rautiainen, R.H. 2013. Distribution and characteristics of occupational injuries and diseases among farmers: a retrospective analysis of workers' compensation claims. American Journal of Industrial Medicine 56(8), 856-869. <https://doi.org/10.1002/ajim.22194>

Karttunen, J.P. & Rautiainen, R.H. 2021. Effects of terminating the premium discount incentive on workers' compensation claims among Finnish farmers. Nordic Meeting on Agricultural Occupational Health & Safety, September 6–8, 2021, Skjetlein Grønt Kompetansesenter, Trondheim, Norway.

[https://www.tts.fi/tutkimus\\_ja\\_kehitys/tutkimushankkeet/maatalous/tyoterveys\\_ja\\_tyoturvaluus\\_maatiloilla\\_-\\_teemasivusto/lisatietoa\\_ja\\_lahteita](https://www.tts.fi/tutkimus_ja_kehitys/tutkimushankkeet/maatalous/tyoterveys_ja_tyoturvaluus_maatiloilla_-_teemasivusto/lisatietoa_ja_lahteita)

LeBauer, D., Wang, D., Richter, K.T., Davidson, C.C., Dietze, M. (2013). Facilitating feedbacks between field measurements and ecosystem models. Ecological Monographs, 83, 133-154. <https://doi.org/10.1890/12-0137.1>

Li, Y., Korhonen, P., Kykkänen, S., Maljanen, M., Virkajärvi, P., Shurpali, N.J., 2023. Management practices during the renewal year affect the carbon balance of a boreal legume grassland. Front. Sustain. Food Syst. 7, 1158250. <https://doi.org/10.3389/fsufs.2023.1158250>

Lindström, I., Lantto, J., Karvala, K., Soini, S., Ylinen, K. & Suojalehto, H. 2021. Occupational & Environmental Medicine 78:793–800. doi:10.1136/oemed-2020-10732

Luke, Economydoctor 2023. <https://portal.mtt.fi/portal/page/portal/economydoctor/>

Mattila, T.E.A., Rautiainen, R.H., Hirvonen, M., Väre, M. & Perkiö-Mäkelä, M. 2020. Determinants of good work ability among organic and conventional farmers in Finland. *Journal of Agricultural Safety and Health*. 26(2): 67-76. (doi: 10.13031/jash.13667) @2020

McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432. <https://doi.org/10.1080/01431169608948714>

Merisalu, E., Leppälä, J., Jakob, M. & Rautiainen, R.H. 2019. Variation in Eurostat and national statistics of accidents in agriculture. *Agronomy Research* 17(5), 1969–1983. doi.org/10.1515/AR.19.190.

MSI At-Sensor Reflectance Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 12(10): 4038–4048.

Nevalainen, O., Niemitalo, O., Fer, I., Juntunen, A., Mattila, T., Koskela, O., Kukkamäki, J., Höckerstedt, L., Mäkelä, L., Jarva, P., Heimsch, L., Vekuri, H., Kulmala, L., Stam, Å., Kuusela, O., Gerin, S., Viskari, T., Vira, J., Hyväluoma, J., Tuovinen, J.-P., Lohila, A., Laurila, T., Heinonsalo, J., Aalto, T., Kunttu, I., and Liski, J. (2022) Towards agricultural soil carbon monitoring, reporting, and verification through the Field Observatory Network (FiON), *Geosci. Instrum. Method. Data Syst.*, 11, 93–109, <https://doi.org/10.5194/gi-11-93-2022>

Oliveira, R. A., Näsi, R., Korhonen, P., Mustonen, A., Niemeläinen, O., Koivumäki, N., ... & Honkavaara, E. (2024). High-precision estimation of grass quality and quantity using UAS-based VNIR and SWIR hyperspectral cameras and machine learning. *Precision Agriculture*, 25(1), 186-220.

Palosuo, T., Heikkinen, J., and Regina, K. (2015). Method for estimating soil carbon stock changes in Finnish mineral cropland and grassland soils. *Carbon Management*, 6(5–6), 207–220. <https://doi.org/10.1080/17583004.2015.1131383>

Pitkänen, J., 2023. Estimating biomass of silage grass production parcels using an uncrewed aerial system and satellite remote sensing. Aalto yliopisto. Master's thesis. <https://urn.fi/URN:NBN:fi:aalto-202305283432>

Rouse, J.W., Haas, R.H., Schell, J.A. & Deering, D.W. 1973. Monitoring Vegetation Systems in

Ruokavirasto, 2023. Paikkatietoa sisältävä kasvuohjelma 2021/2022. <https://www.ruokavirasto.fi/tietoa-meista/avointieto/paikkatietoaineistot/>

Shi, T. & Xu, H. 2019. Derivation of Tasseled Cap Transformation Coefficients for Sentinel-2

Termonen, M., Kykkänen, S. P. K., Mustonen, A., Seppänen, M., Virkajärvi, P. (2022). Combination of cattle slurry and mineral n fertilizer for efficient grass production in Finland. In *Proceedings of the 29th General Meeting of the European Grassland Federation Caen, France, Grassland at the heart of circular and sustainable food systems* (Vol. 27, pp. 737–739).

the Great Plains with ERTS (Earth Resources Technology Satellite). *Proceedings of 3rd*

TTL, 2022. Occupational diseases and suspected occupational diseases 2018

United Nations. Department of Economic and Social Affairs. Sustainable Development Goals. Available at: <https://sdgs.un.org/goals>

van den Berg, T. I., Elders, L. A., de Zwart, B. C., & Burdorf, A. (2009). The effects of work-related and individual factors on the Work Ability Index: a systematic review. *Occup Environ Med*, 66, 211-220. doi:10.1136/oem.2008.039883

Vekuri, H., Tuovinen, J.-P., Kulmala, L., Papale, D., Kolari, P., Aurela, M., Laurila, T., Liski, J., & Lohila, A. (2023). A widely-used eddy covariance gap-filling method creates systematic bias in carbon balance estimates. *Scientific Reports*, 13(1), 1720. <https://doi.org/10.1038/s41598-023-28827-2>

Viskari, T., Pusa, J., Fer, I., Repo, A., Vira, J., Liski, J. (2022). Calibrating the soil organic carbon model Yasso20 with multiple datasets. *Geoscientific Model Development* 15, 1735–1752. <https://doi.org/10.5194/gmd-15-1735-2022>

Weiss, M. and Baret, F. (2016) S2ToolBox Level 2 products: LAI, FAPAR, FCOVER, [https://step.esa.int/docs/extra/ATBD\\_S2ToolBox\\_L2B\\_V1.1.pdf](https://step.esa.int/docs/extra/ATBD_S2ToolBox_L2B_V1.1.pdf)

Wittke, S., Fouilloux, A., Lehti, P., Varho, J., Kivimäki, A., Karhu, M., Karjalainen, M., Vaaja, M., & Puttonen, E. (2023). EODIE — Earth Observation Data Information Extractor. *SoftwareX*, 23.

<https://doi.org/10.1016/j.softx.2023.101421>

Yli-Halla M., Lötjönen T., Kekkonen J., Virtanen S., Marttila H., Liimatainen M., Saari M., Mikkola J., Suomela R., Joki-Tokola E. (2022) Thickness of peat influences the leaching of substances and greenhouse gas emissions from a cultivated organic soil. *Sci. Total Environ.*, 806, <https://doi.org/10.1016/j.scitotenv.2021.150499>

Yli-Viikari, A. & Reinikainen, A. 2022. Ruoantuotannon kestävyys: taloudelliset ja sosiaaliset vaikutukset.

Luonnonvarakeskus, Tietokortti. Available at: [https://www.luke.fi/sites/default/files/2023-](https://www.luke.fi/sites/default/files/2023-04/LUKE_Tietokortti_Ruoantuotannon%20taloudellinen%20ja%20sosiaalinen%20kest%C3%A4vyys_FINAL.pdf)

[04/LUKE\\_Tietokortti\\_Ruoantuotannon%20taloudellinen%20ja%20sosiaalinen%20kest%C3%A4vyys\\_FINAL.pdf](https://www.luke.fi/sites/default/files/2023-04/LUKE_Tietokortti_Ruoantuotannon%20taloudellinen%20ja%20sosiaalinen%20kest%C3%A4vyys_FINAL.pdf)