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REMOTE SENSING DATA APPLICATION TO MONITOR CARBON FARMING PRACTICES

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KEY WORDS: Remote sensing, Multispectral, Synthetic Aperture Radar (SAR), Data fusion, Carbon farming, Sustainable Agriculture, Environmental Monitoring.

ABSTRACT:
Carbon farming, a crucial strategy in mitigating climate change and promoting sustainable agriculture, requires precise monitoring to assess its effectiveness. This study explores the transformative potential of remote sensing data, with a focus on the fusion of Multispectral and Synthetic Aperture Radar satellite data, to enhance the precision and efficiency of carbon farming monitoring. Our research addresses the fundamental question: How can remote sensing data optimize the monitoring of carbon farming practices? This question drives our investigation into the practical applications of remote sensing technology in the context of carbon farming. In this article, the research is carried out in Lithuania, which is often covered with clouds or their shadows, so the application of various satellite images becomes even more meaningful. The study shows that the use of SAR image fusion for the identification of permanent meadows is appropriate and meaningful. The use of MSI image fusion for the identification of intermediate crops and stubble is also appropriate, but more research is needed that focuses on distinguishing these practices from other spectrally very similar practices.

1. INTRODUCTION

1.1 Background and Significance

The concept of "climate change," increasingly observed and discussed in recent times, represents one of the most significant challenges and threats of this century. More and more scientists claim that the signs of climate change are perceptible to nearly every inhabitant, most commonly manifested as meteorological extremes. These include exceptionally severe storms that devastate, incinerate, and flood human settlements, as well as habitats of flora and fauna. Climate change is intrinsically linked to greenhouse gases (GHGs). These gases, including carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), have the characteristic of trapping heat, thereby elevating the overall temperature of the atmosphere (Lackner et al., 2022). The primary source of GHG is human activities in different sectors as energy, waste, transport, industry and also agriculture. The agriculture sector is a different that it not only emits emissions, but also has the potential sequestrate part of them from the atmosphere through sustainable farming practices (Ellis, 2023). Sustainable farming practices that concentrate into carbon sequestration are called carbon farming practices.

Carbon farming emerges as a critical response to this environmental crisis. It is an agricultural method aimed at sequestering atmospheric CO_2 and storing it in soil and vegetation. Through practices like improved crop rotation, cover crops, conservation tillage, agroforestry, and so on carbon farming not only captures CO_2 but also enhances soil health, biodiversity, and water retention (USDA, 2023). The significance of carbon farming lies in its dual role: it contributes to mitigating climate change by reducing atmospheric GHG levels and simultaneously supports sustainable agriculture. As the world grapples with the need to reduce emissions, carbon farming presents a nature-based solution that aligns agricultural productivity with environmental stewardship.

In addition to all the benefits of carbon farming for the soil and its condition, it is also important to mention that there is growing interest in creating incentives for enhancing soil carbon, including through emissions trading (Gray et al., 2022), also, European Union countries encourage farmers to start or continue such activities with various benefits.

Carbon farming, at the intersection of sustainable agriculture, climate change mitigation, and sustainable business necessitates accurate continues monitoring to ensure its progress, efficiency (Basso, 2022) and kind of control that it do not turn into simple greenwashing.

Analysing scientific literature, several aspects can be distinguished why it is important to constantly monitor carbon farming practices and their efficiency (Basso, 2022; Brockett et al., 2019; Mandal et al., 2022; Melillo & Gribkoff, 2021; Nguyen, 2021; USDA, 2023).

Climate change mitigation. One of the main goals today is climate change mitigation and carbon farming practices, such as improved land management, increased soil organic carbon, improved soil health, play an important role in removing CO2 from the atmosphere, which is one of the main GHG gases. Monitoring carbon farming practices helps quantify and validate their impact on reducing CO2 levels in the atmosphere.

Improving Soil Health. Applying carbon farming practices on farms not only contributes to climate change mitigation, but also has significant benefits for improving soil health. Practices like cover cropping and reduced tillage increase organic matter in the soil, enhancing its fertility and structure. Continuous monitoring provides an understanding of whether the practices are effectively contributing to soil health.

Policy Making. For policy and law makers, continuous monitoring of such practices provides essential data to shape effective environmental and agricultural policies. Timely and correct policy formation ensures compliance with international agreements on climate change, such as the Paris Agreement.

Financial Initiatives and Support. For various economic initiatives, such as carbon credits or other support providers, the main evidence that carbon farming practices are sustainable and effective is continuous monitoring of the situation. In this position, monitoring is important for both parties – the entity providing support and the entity receiving it.

R&D. Continuous monitoring provides scientists with valuable data for various ongoing studies related to agriculture, climate change or environmental protection. Ongoing monitoring helps understand the long-term impact of carbon farming practices and allows for the development of new, effective methods.

Global Food Security. It was mentioned above that carbon farming practices help improve soil health. Better soil health makes it possible to significantly reduce the use of various pesticides and of course to grow a larger amount of crops. Therefore, it is important to monitor whether these practices are followed and whether they are really effective on a particular farm and can meet future food needs.

Adaptation to Climate Change. In addition to mitigation, it is equally important to adapt to the ongoing effects of climate change. Healthy soil has more organic matter, which can better withstand extreme weather conditions, reducing the vulnerability of farms to droughts and floods.

Carbon and sustainable farming practices in general should obviously be constantly monitored, but there are some challenges here.

1.2 Challenges in Carbon Farming Monitoring

Carbon sequestration is a long-term process. It requires continuous and long-term monitoring to understand the true impact of carbon farming practices, which can be resource-intensive. The traditional way to assess the effectiveness of carbon farming practices is through physical sampling in the fields. This method is quite expensive and time-consuming, so samples are often taken with a big gap of a year, for example every 5 years, because otherwise it is not economically worthwhile (Gray et al., 2022). Physical sampling is considered to be one of the most accurate methods of determining soil carbon and monitoring the overall sequestration situation in fields, but this method may also not always be accurate. Soil carbon content can vary greatly over short distances and at different depths, making it difficult to identify sampling sites that are accurately representative on a wider scale. It is important to consider the topography of the area, soil type and texture, climate of the area, weather, etc. when selecting sampling sites (Brady & Weil, 2016).

Physical measurements of the soil are recommended in any case, because time to time need accurately as possible to estimate the carbon content of the soil, but with the help of remote sensing, it is possible to monitor the fields of sustainable farming continuously without interruption and see earlier if the applied practices are beneficial, if the soil condition, crop condition, and yield increase. Several main advantages of using satellite images can be distinguished: large territorial coverage, consistent and uniform coverage of the territory, economic benefits. The use of satellite images also has some disadvantages. As already mentioned, carbon farming practices are a long process and require long and very frequent monitoring of the ground surface. In this situation, priority is given to free and publicly available satellite data sources, otherwise monitoring would become an extremely expensive process. Currently, the best resolution publicly available product is data from the Sentinel satellites. Although the Sentinel satellites have a sufficiently high resolution (grid size of 10 m), this may still be too low a resolution to identify smaller objects, smaller farmers' plots or certain practices such as reduced tillage.

Clouds are also a big problem, which can disrupt continuous monitoring. In the territory of Lithuania, there are cases when multispectral images may not be available for three or even more months due to cloud cover. The loss of intermediate images from continuous monitoring can make it difficult to keep track of what was done when - for example, when the crop was harvested, when the land was cultivated and whether it was cultivated, etc.

One of the disadvantages is the fact that satellite images "see" only the surface of the earth and cannot make any observations under the upper layer of the earth. In terms of carbon farming practices and soil carbon content, it would be useful to identify and monitor the situation at a certain depth in the soil, but satellite imagery is not suitable for this.

Observing carbon farming practices remotely in some cases becomes a real challenge for scientists. Some practices may not be visually very different from a farmer's normal activities, such as intermediate crops and winter crops, or some tillage, such as mill-till and mulch-till, may be visually difficult to distinguish.

1.3 Study Objectives and Approach

This study explores the potential of remote sensing data, with a focus on the fusion of multispectral (MSI) and Synthetic Aperture Radar (SAR) satellite data, to enhance the precision and efficiency of carbon farming monitoring. In this article, the research is carried out in Lithuania, which is often covered with clouds or their shadows, so the application of various satellite images becomes even more meaningful.

Various remote sensing data such as panchromatic, multispectral, hyperspectral, SAR images covering different parts of the electromagnetic spectrum are obtained from different earth observation satellites. These data can be processed and used to solve various tasks, but in many cases, using only one type of images, the obtained result may not be sufficient to solve the task. Therefore, in order to have a more detailed understanding of the observed and analyzed surface of the earth, to obtain more information about the observed object, the fusion of different date of data becomes an excellent solution.

Analysing research papers of scientists (Andrade et al., 2021; Chanussot et al., 1999; De Laurentiis et al., 2021; Fitrzyk, 2019; Higgins et al., 2021; Lu et al., 2010; Marí et al., 2023; Metrikaityte et al., 2022; Pal et al., 2019; Shamaoma et al., 2023), in which they applied the fused SAR and/or MSI images for land use land cover (LULC) segmentation, it can be seen that the fusion of multiple data produces more accurate results, but the percentage of accuracy varies in some cases quite strongly. This may be influenced by the satellite images used, different land cover classes distinguished, and different classification algorithms used. It is also very important to pay attention to the fact that in the analyzed articles, research is carried out on territories of various areas, which are located in different geographical areas, this may also be the reason why the results obtained by different scientists are so different.

In this study, three different agricultural activities that contribute to carbon sequestration in agriculture were selected for analysis - permanent meadows, intermediate crops and stubble. These activities and their monitoring are of interest to the government, farmers and scientists alike.

Lithuania is committed to the European Union not to cultivate and/or restore permanent meadows. Permanent pasture or meadow means an area of land which has been under permanent grasses or has not been cultivated naturally for five or more years and which is intended for the grazing of livestock, for grass or for grass production and which can be reseeded without being sown. A permanent pasture or meadow may contain individual trees and/or shrubs (Nacionalinė mokėjimo agentūra prie Žemės ūkio ministerijos, 2023b). Permanent pastures or meadows contribute to agricultural carbon sequestration thanks to their extensive root system, which stores carbon in the soil. Compared to annual crops, permanent meadows have very little soil disturbance, which helps to maintain a higher level of organic soil carbon. Permanent meadows are also more resilient to climate change, such as drought and extreme weather conditions (Conant et al., 2001).

Intermediate crops, also known as cover crops, are also an important farming practice to increase carbon sequestration and improve soil health. Intermediate crops cover the soil surface with their aboveground mass after harvesting the main crops, thus reducing soil erosion, absorbing soil nutrients, improving soil structure and fertility, and reducing the spread of weeds, diseases and pests on arable land (Nacionalinė mokėjimo agentūra prie Žemės ūkio ministerijos, 2023a; Poeplau & Don, 2015). Farmers who carry out this activity undertake to grow the intermediate crops over the winter, i.e. to sow them by 1 September and maintain them until 1 March of the following year. The intermediate crops may consist of perennial leguminous and bell grasses, oilseeds, leguminous crops, bell cereals or a mixture of these groups of crops (Nacionalinė mokėjimo agentūra prie Žemės ūkio ministerijos, 2023a).

Leaving stubble on the field after harvest is part of extensive farming, where farmers contribute to maintaining biodiversity and a stable and strong ecosystem. Leaving stubble standing over winter reduces the risk of erosion from wind and water, thus protecting the soil and reducing changes in the surface water ecosystem. Stubble is a valuable winter food source for wild birds collecting spent grain and weed seeds (Lietuvos Respublikos žemės ūkio ministerija, 2021). After harvesting, farmers must leave the stubble until 1 March next year.

Farmers must declare these activities each year in order to receive financial support under certain European support programs.

In research by Metrikaityte et al. (2022) shown that fusion of two SAR images is very suitable for change detection. This method has been applied to the detection of permanent meadows. Permanent meadows were chosen as a target because it is expected to be unchanging and farmers cannot start active farming in such areas. Stubbles and intermediate crops, being relatively short and often homogeneous in structure, might not provide enough surface roughness contrast to be effectively distinguished by SAR, especially compared to taller vegetation or structures. SAR images are radar-based and do not provide spectral information in the visible and near-infrared range, which is crucial for identifying different types of vegetation. The spectral signatures of stubbles and intermediate crops in these ranges are often used to distinguish them from other land cover types, which is not possible with SAR. Optical and multispectral imagery, which provides detailed spectral information, is generally more suitable for identifying and differentiating between various types of crops and agricultural residues.

2. METHOD

2.1 Data Collection Methods

In this study were used synthetic aperture radar (SAR) Sentinel-1 and multispectral (MSI) Sentinel-2 satellite images distributed by the European Space Agency (ESA) (Table 1).

Data fusion	Satellite	Data type	Date
SAR data fusion	Sentinel-1	Level-1 SLC	2019-07-14
	Sentinel-1	Level-1 SLC	2020-07-14
	Sentinel-1	Level-1 SLC	2021-07-15
	Sentinel-1	Level-1 SLC	2022-07-16
	Sentinel-1	Level-1 SLC	2023-07-11
MSI data fusion	Sentinel-2	L2A	2023-08-02
	Sentinel-2	L2A	2023-08-12
	Sentinel-2	L2A	2023-08-15
	Sentinel-2	L2A	2023-10-10
	Sentinel-2	L2A	2023-10-19
	Sentinel-2	L2A	2023-10-25

Table 1. Data sources used in this study

SAR images are classified as active remote sensing, when information about the object under study is obtained by emitting a pulse of electromagnetic radiation and recording the return reflection of the same pulse from the object under study.

Multispectral images are classified as passive remote sensing, which means that the sensor captures the energy emitted by another electromagnetic source (for example, the Sun) and then reflected from the object under study. Multispectral images consist of several monochromatic images of the same image with different spectra, each of which is obtained by photographing the object with a different optical filter. According to the selected filter, the image is passed only from a certain spectrum of electromagnetic wavelengths. Such different monochromatic images are called bands.

Intermediate crops and stubble are activities that take place after a crop has been harvested until the next crop is sown.

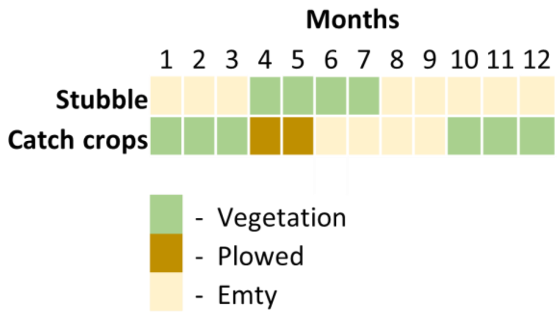

Figure 1. Calendar of stubbles and intermediate crops seasons

Taking into account the periods of farming activity shown in the Figure 1, it is recommended to identify stubble on satellite images in August and intermediate crops in October. Permanent meadows should be green throughout the year apart from the winter season. As SAR satellite images were used to identify permanent meadows, which are less dependent on specific seasonal variations in vegetation compared to optical imagery, the month of July was chosen in the study to identify these areas.

2.2 Data Fusion Technique Overview

The fusion of remote sensing data products has the purpose to make synergistic use of the data. This can have multiple reasons. For example, bands of the visible spectrum from one sensor can be combined with near infrared bands of another. The result of fused data can only be as good as the geographical location of the input products.

The SAR data provided by the ESA have different characteristics when compared to the MSI data, both in terms of their physical properties and the principle of image acquisition, so both images require preprocessing so that they can be combined later.

An essential part of merging is the transfer of data from one raster to another. If the raster distances of the trap pixels and/or the orientation do not match, then you need to either select new rasters or review the image preprocessing process. Ana B. Ruesca and Marco Peters have provided examples of how the pixels of two different rasters mismatch in their tutorial (Ruescas & Peters, 2022). Figure 2 shows examples of three types of overlap: when there is a different distance between two raster pixels (Overlap 1); when there is an overlap between raster pixels (Overlap 2); when there is a different orientation of the rasters (Overlap 3).

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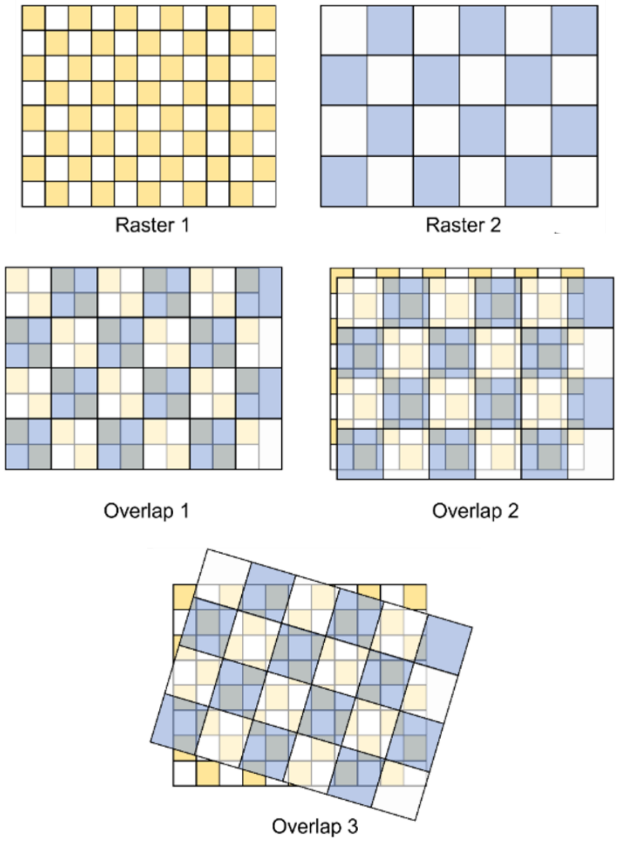

Figure 2. Three types of overlap of 2 rasters with different pixel-spacing (Ruescas & Peters, 2022)

Raster mismatch can be resolved by raster resampling. There are several resampling algorithms available, such as Nearest Neighbor Resampling, Bilinear Interpolation, Bicubic Interpolation and Bisinic Interpolation. In this study, SAR and MSI images of the same grid size are used, so none of the mentioned algorithms will have a significant impact, so the Nearest Neighbor resampling algorithm was chosen, which is dominant among other scientists.

In this study, two image fusion techniques were tested to identify selected carbon farming practices, two SAR images fusion and MSI images of one month fusion.

Fusion of the SAR images is performed using waves coherence, average and difference, and the result is presented as an RGB composite. The SAR images from two different dates are processed in a standard way, their coherence is calculated and additionally the average and difference of the waves also calculated. In the next step, all these three parameters are presented in an RGB composite, where R is the coherence, G is average and B difference. In the resulting RGB image, green areas indicate forests and vegetation, yellow areas indicate urban areas, blue areas indicate changes that have taken place and magenta areas indicate areas where no changes have occurred. The fusion of the two SAR images is particularly suitable for identifying land cover land use changes that have or have not occurred. The areas of permanent meadows should not change over time, so fusion of SAR images from different years should give the same result - no change. The results of the method tested are presented in Section 3.1.

For the MSI image fusion, Sentinel-2 images were used and subjected to standard processing such as atmospheric corrections, cloud and shadow removal, discarding of bands not relevant to the study and calculation of additional indices. The fusion of the images is necessary because of the holes that appear when clouds and shadows are cut out. Three additional indices have been selected for this study - Normalized Difference Turbidity Index (NDTI), Red-Edge Normalized Difference Vegetation Index (NDVIre), Modified Normalized Difference Water Index (MNDWI).

The NDTI index is useful for measuring soil and vegetation moisture, and provides a good contrast between different vegetation types. The NDVIre index reflects strongly on dead foliage and is useful for identifying vegetation types, soils and urbanised areas, but it also indicates limited water infiltration and reflects poorly on green vegetation, which is rich in chlorophyll. The MNDWI index provides an excellent contrast between clear and turbid water and penetrates relatively well into clear water, helping to highlight plants on the surface of water bodies and vegetation, reflecting green light more strongly than any other colour of the visible spectrum.

$$NDTI = (SWIR\ 1 - SWIR\ 2)/(SWIR\ 1 + SWIR\ 2) \tag{1}$$

$$NDVIre = (RedEdge\ 1 - Red)/(RedEdge\ 1 - Red) \tag{2}$$

$$MNDWI = (Green - SWIR\ 1)/(Green + SWIR\ 1) \tag{3}$$

where SWIR 1 is Sentinel-2 B11 band
SWIR 2 is Sentinel-2 B12 band
RedEdge 1 is Sentinel-2 B05 band
Red is Sentinel-2 B04 band
Green is Sentinel-2 B03 band

Supervised classification of MSI fusion images was performed to identify the objects to be analysed in the study. Random Forest algorithm was used for classification. A sample library from different national datasets was created for classification training and validation:

- data on farmers' declarations of land for the years 2021, 2022 and, separately, for stubble and intermediate crops;
- forest cadastre data;
- cadastre of rivers, lakes and ponds;
- Corine Land Cover data;
- data set on the farmland, cropland and crop types.

Figure 3 shows the library of created samples. The results of the classified MSI images are presented in Section 3.2.

Source	COD	S2_4	S2_3	S2_2	S2_5	S2_6	S2_7	S2_8	S2_8A	S2_11	S2_12	NDTI	NDVIre	MNDWI
Stubble	13	1346	897	647	1623	1785	2000	2302	2504	3151	2536	1081	932	-5568
Stubble	13	1346	860	618	1518	1663	1932	2236	2341	3059	2467	1071	601	-5611
Stubble	13	1346	888	641	1649	1782	2119	2344	2542	3143	2505	1130	1012	-5594
Stubble	13	1346	926	611	1803	2188	2550	2796	2977	2655	1805	1906	1451	-4828
Stubble	13	1346	856	602	1610	1737	1988	2208	2384	2830	2008	1699	893	-5355
Stubble	13	1346	885	600	1662	1841	2092	2308	2553	2837	1957	1836	1051	-5244
Stubble	13	1346	987	677	1784	2315	2642	2920	2993	3571	2538	1691	1399	-5669
Stubble	13	1346	954	733	1573	1754	1969	2136	2268	2789	2072	1475	777	-4902
Stubble	13	1348	902	639	1595	1693	1966	2156	2330	2974	2144	1622	839	-5346
Stubble	13	1348	845	576	1556	1754	2019	2260	2444	2754	1867	1918	716	-5304
Stubble	13	1348	873	583	1699	1859	2070	2350	2526	2808	1947	1811	1152	-5256
Stubble	13	1350	1122	827	1754	2202	2371	2492	2633	3015	2171	1627	1302	-4576
Stubble	13	1350	971	761	1653	1878	2171	2230	2522	2788	1781	2204	1009	-4834
Stubble	13	1350	1019	749	1609	1913	2024	2292	2404	2637	1631	2357	875	-4426
Stubble	13	1350	998	789	1694	1959	2160	2268	2463	2933	1905	2125	1130	-4922

Source	COD	S2_4	S2_3	S2_2	S2_5	S2_6	S2_7	S2_8	S2_8A	S2_11	S2_12	NDTI	NDVIre	MNDWI
Intermediate crops	15	425	803	370	1389	3518	3919	4704	4096	2334	1182	3276	5314	-4880
Intermediate crops	15	425	780	357	1419	3480	3856	4592	4061	2393	1195	3338	5390	-5084
Intermediate crops	15	426	637	245	1218	2700	3060	3438	3399	1670	850	3254	4818	-4478
Intermediate crops	15	426	637	242	1274	3100	3375	3652	3810	1749	890	3255	4988	-4661
Intermediate crops	15	426	698	293	1282	2919	3386	3686	3614	1851	934	3293	5012	-4523
Intermediate crops	15	426	739	352	1480	3980	4200	4504	4475	2140	1076	3308	5530	-4866
Intermediate crops	15	426	750	342	1433	3693	4172	4252	4346	2110	1060	3312	5417	-4755
Intermediate crops	15	426	650	265	1246	2777	3233	3438	3564	1680	840	3333	4904	-4421
Intermediate crops	15	426	1011	363	1776	4026	4343	4996	4535	2205	1088	3392	6131	-3713
Intermediate crops	15	426	763	345	1437	3913	4262	4736	4422	2100	1032	3410	5427	-4670
Intermediate crops	15	426	805	317	1550	3666	4001	4276	4279	1938	945	3444	5688	-4131
Intermediate crops	15	426	958	381	1688	5012	5448	5760	5637	2308	1119	3469	5970	-4133
Intermediate crops	15	426	794	295	1511	3859	4262	4576	4514	1907	924	3472	5601	-4121
Intermediate crops	15	426	986	357	1784	4245	4550	4948	4732	2242	1080	3498	6145	-3891
Intermediate crops	15	426	764	325	1483	3947	4414	4548	4532	2090	1005	3506	5537	-4646

Figure 3. Example of library of created samples for satellite image classification. Source is the type of activity in field; S2_4, S2_3…S2_12 are Sentinel-2 Band 4, 3…12; NDTI, NDVIre, NDWI – calculated indexes.

2.3 Study Area

An area in north of Lithuania was selected for the study (Fig. 4). The study area spans approximately 3883,4 km^2 and includes both urban and rural landscapes. This territory was chosen because of its extensive farming. Crops are the main focus of farming in this region due to its high productivity, so there are a large number of farmers who have been applying or are starting to apply sustainable or carbon farming practices for some time.

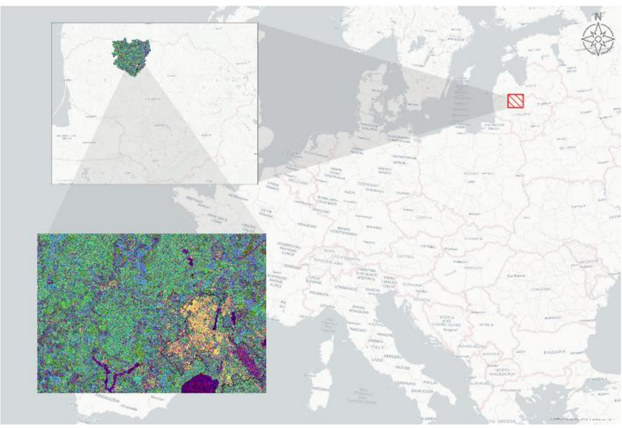

Figure 4. Study area

3. RESULTS

3.1 SAR Data fusion Analysis Findings

For the identification of permanent meadows, 5 years of SAR satellite images of the vegetation peak were selected, from 2019 to 2023. An annual assessment of the changes in the area was carried out, as well as an overall assessment of the whole period, i.e. the situation between 2019 and 2020, between 2020 and 2021, between 2021 and 2022, between 2022 and 2023 and finally between 2019 and 2023. The result of the SAR image fusion is presented as an RGB composite, with green indicating forests and vegetation areas, yellow indicating urban areas, blue indicating changes that have occurred, and magenta indicating areas where no changes have occurred.

The results (Fig. 5) show that SAR image fusion alone is suitable for identifying areas of permanent meadows, but that this requires time series analysis. The analysis of the fusion images shows that in the individual annual images and in the image for the whole period, the parcels of land that do not fall within our known areas change their values continuously, which vary due to matched or unmatched growing seasons, and only those parcels known to be permanent meadows retain a constant value. Consistent and long-term surveys can not only identify new areas of permanent meadows, but also assess whether some areas have been ploughed or reforested.

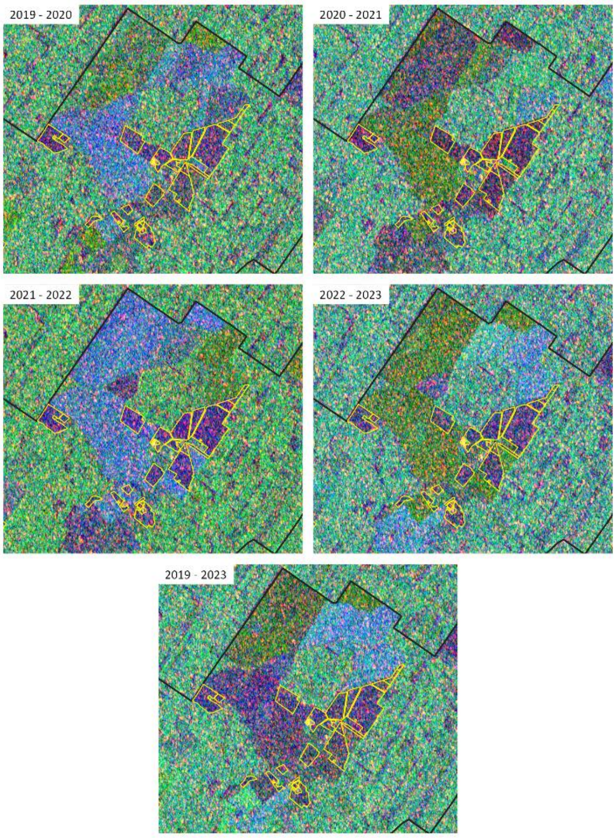

Figure 5. Examples of results, of SAR images fusion. Green colour – forests and vegetation, blue – changes, magenta – no changes, yellow lines – known areas of permanent meadows

3.2 MSI Data Fusion Analysis Findings

For the identification of intermediate crops and stubbles, MSI fusion images from August and October 2023 were used. Examples of the results are shown in Figure 6. The areas shown in the figures are classified into 10 different land cover classes according to their reflectance characteristics and structural properties.

In the example in Figure 6, the identified stubble areas can be seen in light green, which cover most of this area. A visual analysis of the result shows that the classification was successful, but additional calculations were performed to assess the accuracy.

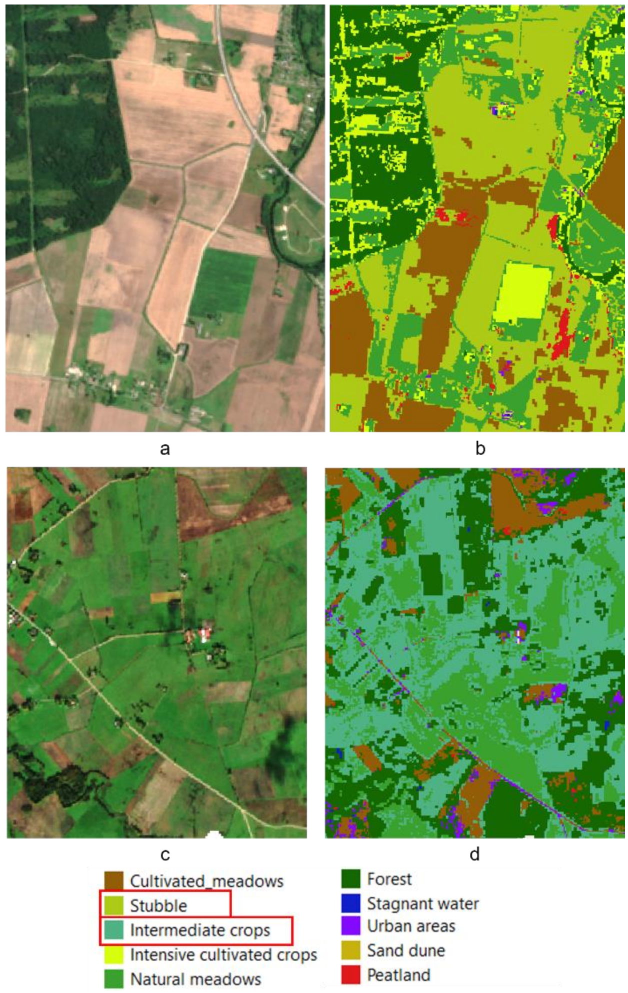

Figure 6. a – RGB image used for stubble areas identification, b – classified image where are identified stubble areas, c - RGB image used for intermediate crop areas identification, d – classified image where are identified intermediate crops

Figure 6 shows an example of the result of the identification of intermediate crops. For the identification of intermediate crops, an area with active farming activity was specifically selected. This area was chosen in order to test whether the use of MSI image fusion and additional indexes can distinguish intermediate crop areas from other visually similar vegetation areas.

To assess the accuracy of classified satellite images, were employed statistical metrics: the weighted mean F1-score and the kappa coefficient.

To evaluate the results, a weighted average of F1 accuracy was used, which is valid for all types of classification algorithms. It is useful to observe the F1 value when the distribution of land use classes is uneven. The F1 value is composed of precision (P) and recall (R) values (IBM, 2023).

$$F1 = 2 * \frac{(P * R)}{(P + R)} \tag{4}$$

where P - over the number of true positives (T_p) plus the number of false positives (F_p)

R - over the number of true positives (T_p) plus the number of false negatives (F_n)

$$P = \frac{T_p}{(T_p + F_p)} \tag{5}$$

$$R = \frac{T_p}{(T_p+F_n)} \quad (6)$$

F1 values are interpreted as a measure of the overall performance of the model, ranging from 0 to 1, where 1 is the best model result and below 0,5 the result is minimal. This is balanced by the ability of the model to capture positive cases and be accurate (Allwright, 2022).

The kappa coefficient, or Cohen's kappa, measures the agreement between the classified image and a reference image, adjusting for the possibility of the agreement occurring by chance. A higher kappa value indicates a stronger agreement beyond chance. In our study, the kappa coefficient provides an essential measure of the overall reliability of the classification, giving us insight into how effectively our classification model performs in comparison to random chance (McHugh, 2012).

Below provided a list of interpreting the kappa coefficient and the reliability of the data, which helps to better understand the results obtained:

- 0-0,2 – None;
- 0,2-0,4 – Minimal;
- 0,4-0,6 – Weak;
- 0,6-0,8 – Moderate;
- 0,8-0,9 – Strong;
- above 0,9 – Almost Perfect.

Formula for calculating the Kappa coefficient:

$$K = \frac{N\sum_{i=1}^{n} X_{ii} - \sum_{i=1}^{n} X_{i+}X_{+i}}{N^2 - \sum_{i=1}^{n} X_{i+}X_{+i}} \quad (7)$$

where N - amount of calculations
n - the number of rows and columns of pixels in the matrix
X_{ii} - the number of calculations in row i and column i
X_{+i}, X_{i+} - total number of columns and rows

The accuracy results are presented in Table 3.

Class	F1
August result for stubble area. **Kappa = 0,87**	
Cultivated meadows	0.66
Stubble	**0.61**
Intensive cultivated crops	0.91
Natural meadows	0.85
Forests	0.99
Stagnant water	1.00
Urban areas	0.89
Sand dunes	0.99
Peatlands	0.97
October result for intermediate crop area. **Kappa = 0,86**	
Cultivated meadows	0.89
Intermediate crops	**0.84**
Natural meadows	0.66
Forests	0.90
Stagnant water	0.97
Urban areas	0.82
Sand dunes	1.00
Peatlands	0.38

Table 2. Results of classifications of stubble and intermediate crop areas

The accuracy of stubble identification in the classified image on August month was quantified using the F1-score, a measure that combines precision and recall. Our results indicated an F1-score of 0.61 for the stubble class. This suggests a moderate level of accuracy, implying that while a majority of the stubble areas were correctly identified, there were instances of misclassification or missed detections. The kappa coefficient for the entire classification process was calculated to be 0.87. This high value indicates a strong agreement between the classified results and the reference data, suggesting that the overall classification, despite the challenges in accurately identifying stubble, was generally reliable and consistent.

The October results when intermediate crops were identified show an F1-score of 0.84 for this class. This high score indicates a strong accuracy level, suggesting that most intermediate crop areas were correctly identified with few instances of misclassification.

The overall kappa coefficient for the classification was 0.86, reflecting a high level of agreement between the classified image and reference data. This suggests that the classification process was generally reliable and consistent, despite the specific challenges in accurately identifying intermediate crops.

4. DISCUSION & CONCLUSIONS

In this study, we utilized SAR and MSI data to identify and monitor different carbon farming practices, specifically focusing on permanent meadows, stubble, and intermediate crops. The results provide valuable insights into the efficacy of these remote sensing techniques for agricultural land monitoring.

The analysis of the results shows that the use of SAR image fusion for the identification of permanent meadows is appropriate, but requires specific data processing and long-term monitoring. At the same time, we can see that the result is good and suitable for visual analysis, but the classification of such an image can be a challenge because the values of the individual grids in the same plot are quite heterogeneous. Additional processing may be required to classify this result and use it for further calculations and analysis.

Focusing on the stubble category within the broad land use land cover classification system has highlighted the difficulties in accurately identifying crop residues using satellite imagery. The average F1 score of stubble shows that distinguishing it from other land cover types is a difficult task, which is further complicated in different agricultural areas. However, the robust kappa coefficient shows that our classification model is very consistent across categories, which confirms the overall effectiveness of our approach.

To improve the accuracy and reliability of our classification process, especially for stubble detection, it is necessary to continuously improve and further analyse our algorithms. The need to improve stubble classification is underlined by the moderate detection performance, which suggests that more sophisticated imaging techniques or additional data should be included in future research.

The examination of intermediate crops through an extensive land use land cover classification process has provided valuable insights. The high F1 score of the model reflects its competence in accurately classifying intermediate crops. However, due to the lower reliability index, these results have to be interpreted with caution as it indicates that the intermediate crop category may be misclassified. The significant kappa coefficient reaffirms the consistency of the model across different land use land cover types. It has also been observed that intermediate crops correlate quite strongly with arable land and natural meadows. The correlation with arable land is obtained when the attempt to identify the intermediate crops was premature, i.e. before they had germinated. In contrast, once the crop has sufficiently matured, it becomes difficult to distinguish it from grassland.

These results highlight the challenges of classifying agricultural landscapes using satellite images, especially for intermediate

crops, which have different spectral characteristics at different growth stages and species. To increase the accuracy of identification of stubble and intermediate crops in future iterations of the model, it will likely be necessary to integrate additional spectral data or temporal information in order to more effectively identify the unique characteristics of these farming activities.
Future studies plan to include more and more different carbon farming practices in the identification process. Given the reasonably good results of the SAR fusion analysis, it is planned to concentrate on a wider application of SAR imagery, which would greatly enrich and facilitate observations in areas such as Lithuania, where observations could be carried out continuously and independently of meteorological conditions.

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