Fluctuations in Groundwater and Peat Emission During the Early Growing Season of Clay-on-Peat Soils With Different Management Intensities

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ABSTRACT

Peatlands play a crucial role in global carbon storage and climate change mitigation, but they are rapidly degrading due to human activities. This study focuses on peat soils in the province of Friesland, the Netherlands, where intensive land use practices pose a significant threat to peatland ecosystems. The research compares conventional and organic agricultural practices to understand their effects on peat soil management and carbon emissions. The study employs multivariate statistical techniques, including NMDS and PERMANOVA analyses, to examine the relationship between management intensities, environmental variables, and peat emissions. Additionally, fluctuations in groundwater and peat emissions during the early growing season are investigated to gain insights into system dynamics. The findings indicate distinct associations between specific variables and management styles, emphasizing the trade-offs associated with different management strategies. The results of this study provide valuable insights for decision-makers in the agricultural sector, enabling the development of more sustainable land-use strategies that preserve peatlands, minimize carbon emissions, and promote environmental conservation. However, limitations such as the small sample size and time-limited nature of the study should be considered when interpreting the results. Future research should expand the sample size, extend the sampling period, and consider the cumulative effects of weather patterns to enhance the generalizability and understanding of peatland dynamics.

INTRODUCTION

Soil is a crucial component of the terrestrial environment, providing essential ecosystem services such as food production, water storage and purification, nutrient cycling, climate regulation, and habitat for biodiversity (Berendse, 2001; Schröder, 2016). Soils are also integral to the climate system, constituting the largest organic carbon pool in the terrestrial biosphere. The soil organic carbon pool contains about twice as much carbon as the atmosphere, making it a crucial player in the global carbon cycle (Jobbágy and Jackson, 2000).

Peat soils are wetland soils that occur through the accumulation of partially decomposed plant material over thousands of years (Turetsky et al., 2015). Peatlands are critical in the context of soil carbon storage and climate change, despite covering only about 3% of the Earth's surface. They store approximately one-third of the planet's soil carbon, making them crucial in mitigating climate change by sequestering significant amounts of carbon (Harenda et al., 2018).

Peatlands are the most carbon-dense terrestrial ecosystems globally, storing up to twice as much carbon as all the world's forests combined (IPCC, 2019).

Peatlands across the globe are rapidly degrading due to human activities, such as draining for agriculture and other land uses. This has resulted in the release of significant amounts of carbon into the atmosphere, estimated to be approximately 15% of the world's peatlands (IPCC, 2019). Additionally, degrading peat soils release methane into the atmosphere, accounting for more than 8% of global anthropogenic greenhouse emissions (IPCC, 2019). Peatland degradation is a major contributor to climate change and significantly impacts the region's resilience to climate-related threats such as flooding, droughts, and salinisation. Therefore, it is urgent to manage and restore peatlands sustainably to prevent further degradation and carbon emissions. Studying peat management in an agricultural landscape is crucial for developing sustainable land use practices, given the importance of peatlands in carbon storage and climate change mitigation, as well as their significance for biodiversity conservation, and can contribute to achieving global climate goals.

One region where peat degradation is a major concern is Friesland, a coastal province north of the Netherlands where around 70,000 ha is part of the peat meadow area (Grondwateratlas Fryslân, 2020; Boer, et al., 2019). Approximately 52,000 ha of this area is dedicated to agricultural land (Grondwateratlas Fryslân). Friesland is recognized as a significant agricultural region, encompassing approximately 229,000 ha of total agricultural land in 2010. Among this land, a significant portion, around 23%, consists of peat soils primarily used for grass production by dairy farmers, particularly in the peat meadow areas (Deru et al., 2017; Archive: Agricultural Census in the Netherlands - Statistics Explained, n.d.).

Intensive land use practices in Friesland necessitate the lowering of groundwater levels to enhance aeration of the topsoil and improve the load-bearing capacity, facilitating optimal crop growth and livestock production. However, this agricultural practice renders the peat soils highly susceptible to degradation. The degradation of peat soils not only leads to a decrease in their capacity to store carbon but also presents significant environmental concerns with implications for climate change mitigation (IPCC, 2019). Moreover, the low groundwater levels in areas with peat soils result in the natural drainage of the higher-lying sandy soils in the southern and southeastern parts of the province, further exacerbating the problem (de Mulder, 2019).

To address these challenges, the study will focus on peat soils within the province of Fryslân. A comprehensive comparison will be made between conventional and organic agricultural practices as they represent two distinct approaches to land-use management and directly impact the hydrology of peat soils (Page & Baird, 2016). The conventional agricultural approach primarily emphasises maximising yield and production efficiency. In contrast, the organic approach adopts a more sustainable and integrated approach, prioritising soil health, biodiversity, and long-term sustainability (Zaller, 2018).

By examining and contrasting the effects of these two approaches on management and carbon emissions of peat soils, this study aims to gain a deeper understanding of the effects of management practices on peat soils. The findings will provide valuable insights to inform decision-making in the agricultural sector. Understanding how conventional and organic farming practices influence the hydrological conditions and carbon emissions in peatlands will contribute to the development of more sustainable land-use strategies. Armed with this knowledge, policymakers, farmers, and land managers can make informed choices that promote the preservation and restoration of peatlands while minimising CO2 emissions and their impact on the environment.

Attempts are being made to reverse peat degradation in Friesland by raising groundwater levels to combat the problem of CO2 emissions resulting from the oxidation of carbon in the soil. Raising the water table promotes anoxic conditions in the soil, slowing down the oxidation of carbon and thereby reducing the rate of CO2 emissions (Chimner & Cooper., 2003). However, it is important to understand the dynamics of peatlands to manage them effectively. Knowledge of the temporal and spatial variability in peat emissions is essential for understanding the effects of land-use practices on the carbon cycle and predicting future emissions (Linden et al., 2014). Therefore, this study aims to investigate fluctuations in groundwater and peat emissions during the early growing season on grassland soils on two land-use intensities in Friesland to understand the system dynamics better and inform management decisions.

This research will therefore answer the question what the effect of different management intensities is on the functions and on the CO2 emissions of peat soils is.

METHODS

Study Site

This paper aims to investigate the relationship between agricultural practices and environmental impacts on peat soils in Friesland. To achieve this, fieldwork was conducted in six neighbouring fields located in Friesland, three

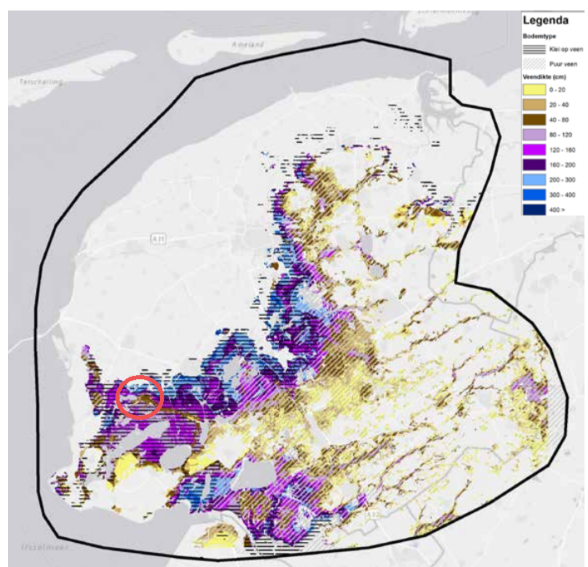


Fig. 1 Map of Frisian peat soil and clay-on-peat soil, the red circle emphasises the area our research was conducted in.

are classified as extensive and three are classified as intensive agriculture based on land management including fertiliser application. All the fields were located on clay over peat soils, and previous research (Kraamwinkel et al., in progress) suggests that the general soil type is similar, but management practices differed significantly.

Fieldwork

To collect data, three visits were made. from, end of February to the end of April to catch the variation of the growing season so we had three/four weeks between the field days. During these visits measurements were taken at three locations per field - two metres from the ditch, seven metres from the ditch, and the middle of the field, this is to look at the effect of the ditchwater on the groundwater level and thus the co2 emissions. These measurements included ditch water level, groundwater level, the thickness of the clay layer, the thickness of the peat layer, soil moisture in the upper 10 cm, penetration resistance in the upper 10 cm, vegetation height, grass/herbs ratio, and CO_2 emissions. All our equipment has been calibrated according to the specifications that are in the manuals of each instrument.

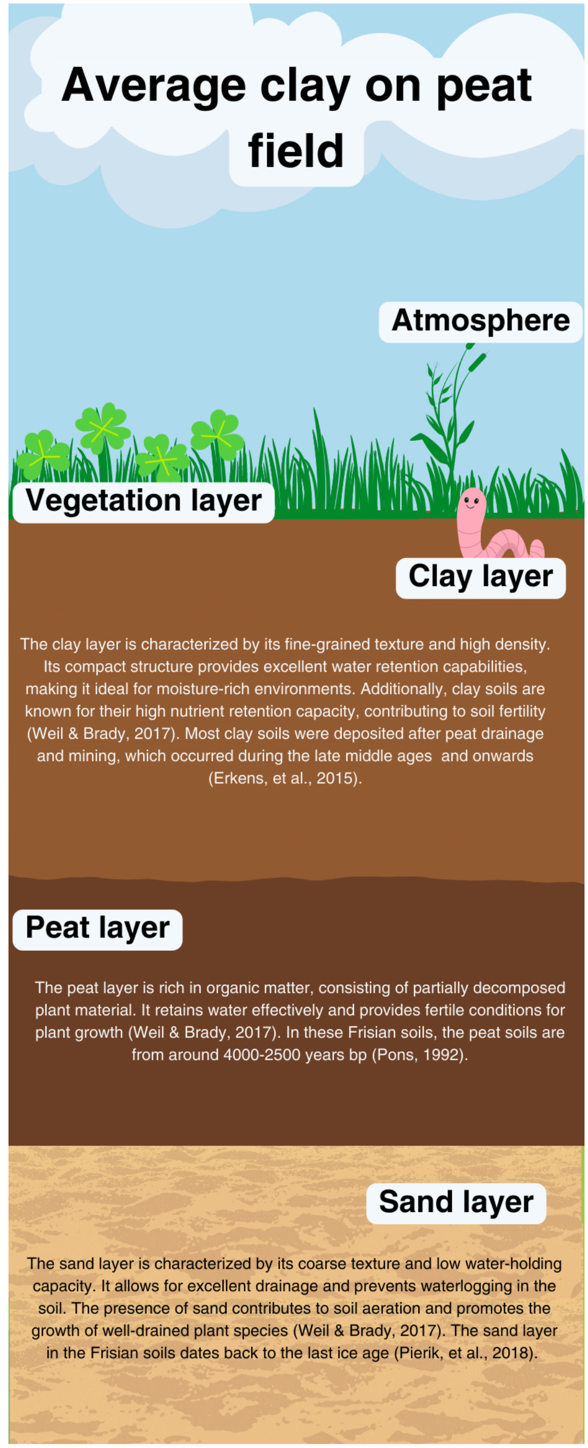


Fig. 2 An infographic of the general soil structure in this research

Ditch water level

To determine the ditch water level of the fields, we used a maximum extended soil core and a measuring rod. The process involved placing the soil core on the ground and using the measuring rod to determine the height difference between the bottom of the core and the ditch water level measured in cm.

Groundwater level and Soil profile

The groundwater level was measured using the Edelman auger for sand from Eijkelkamp. This tool is designed to extract a soil profile to examine the soil. It's not made for groundwater measures. However, we used the auger to estimate where the groundwater level started. The Edelman auger consists of a metal shaft with a spiral-shaped tip that can be screwed into the soil and a handle that allows the auger to be rotated and dug into the soil.

The Edelman auger was used to extract a soil profile at each of the three locations in each field to take the measurements. The auger was screwed into the soil until the sand layer was reached. This gave us the data needed to determine the thickness of the clay and peat layer. The soil profile was carefully examined to determine the water table's depth, and this value was recorded as the groundwater level.

Soil moisture

Fig. 3 The Thetaprobe standard set from Eijkelkamp

The Thetaprobe standard set from Eijkelkamp was used to measure soil moisture at random locations on the measured latitude of the field. This tool is designed to measure the volumetric water content of the soil, which indicates the amount of pore space filled with water instead of air. The Thetaprobe comprises a probe with three needles inserted into the soil and a handheld reader that displays moisture readings.

The Thetaprobe was inserted into the soil to a depth of 10 cm to take the measurements. Each location was measured three times, resulting in nine measurements per field. The average of the three measurements at each site was calculated and used for further analysis.

The measurement was taken three times at each location to account for spatial heterogeneity and variability within the soil. Soil properties such as soil moisture can vary significantly within a field, even at a small scale. By taking multiple measurements at each location, the aim is to capture this variability and obtain a more representative average value.

Spatial heterogeneity refers to the variation in soil properties across space, meaning that different locations within the field can have different soil characteristics. This can be influenced by factors like soil type, topography, vegetation cover, and historical land use. By taking multiple measurements at each location, the researchers can assess the extent of spatial heterogeneity and understand how soil properties vary within the field.

The Thetaprobe uses capacitance sensing technology to measure the dielectric constant of the soil, which is related to the soil moisture content. The probe sends a high-frequency electromagnetic signal between the three needles through the soil. The amount of water in the soil affects the dielectric constant, causing changes in the electromagnetic signal detected by the probe. The handheld reader displays the moisture readings in percent volume of water in the pore space, providing an accurate measure of the soil moisture content.

Penetration resistance

Penetration resistance was measured using the hand penetrometer for top layers, type IB from Eijkelkamp. This tool is designed to measure the resistance of the soil to penetration, providing an indication of soil compaction and the mechanical strength of the soil.

Fig. 4 Penetro-meter

The device used for measuring cone resistance is pushed into the ground at random selected locations to a depth of 10 cm. The scale on the side of the penetrometer displays the force required to achieve this depth in cm. Later on, the force measurements are converted to cone resistance in N/cm^2 using the formula specified in the handbook, considering the cone size and the spring size used in the field.

To ensure the accuracy and reliability of the measurements, we took three readings at each location in the field. The readings were taken on the same day to minimise any variation due to environmental factors. The average of the three readings at each location was calculated, and this value was used to represent the penetration resistance.

Vegetation height

To measure vegetation height, we used a ruler and took three random samples at each of the three locations within each field. The location to measure the vegetation height was determined randomly by placing the measuring rod. At that particular location, we measured the height of the tallest blade of grass adjacent to the ruler. This process was repeated three times at each location, resulting in nine measurements per field.

The vegetation height measurements were recorded in centimetres and the three measurements at each location were averaged to obtain an overall average vegetation height for each location on the field. It should be noted that vegetation height serves as an indicator of land use intensity, reflecting faster-growing vegetation and higher biomass in more intensively managed fields. This proxy is also useful in monitoring shading, evapotranspiration, and controlling potential effects on CO_2 measurements through photosynthesis.

Grass/Herbs ratio

The ratio of grass to herbs in each field was measured by creating a 50 by 50 cm square plot randomly at each of the three locations in each field. The area was marked out using a ruler, and the predicted percentage of grass and herbs present in the area was estimated. The measurements were taken once at each location, resulting in three measurements per field.

During the estimation, care was taken to differentiate between grass and herb species and to account for bare spaces within the area. The grass and herbs ratio provides important information on the biodiversity of the field, as well as the health of the ecosystem. As it is an indicator of biodiversity which is important for ecosystem health and resilience

CO_2 emissions

To measure CO_2 emissions, we used a CO_2 sensor from Vaisala, Handheld CO_2 Meter GM70, which measured the concentration of

Fig. 5 The CO_2 sensor and the closed chamber

CO_2 particles in the air in parts per million (ppm), this method is called the closed-chamber method (Rayment, 2000). We employed the closed chamber method by setting up a plexiglass box over the soil in two locations per field: one at seven metres from the ditch and one in the middle of the field. A small ventilator circulated the air within the box, ensuring a homogeneous sample for CO_2 concentration measurements.

During a 15 min timespan, the CO2 sensor measured the concentration of CO2 in ppm present in the chamber every 30 seconds particles in the air were measured using a device that recorded the ppm of CO_2. We measured the CO_2 concentration in the air within the box for 15 minutes, and the flux (umol/m^2*s) was calculated using the formula $[(\frac{\Delta CO2}{900}) \times 6.696428571]$ to account for the size of the chamber you go from ppm in a small box to flux per square metre per second , it can even be used to calculate co2 flux in ton/ha year (common unit) . The CO_2 flux is an indicator of the amount of peat oxidation, which releases CO2 and is the main GhG on these fields.

Soil organic matter

The soil organic matter is measured by taking soil samples on the fields and using the method of loss on ignition. This is only done in the first round of fieldwork at the 7 metres and the middle of the field, as the soil organic matter will not change much over time.

After the soil samples were acquired, they were taken to the laboratory, where the samples were divided into 3 small subsamples to make the drying and burning process shorter. The 3 different samples were then averaged later on. Before the soil was put into the ceramic cups, we weighed the ceramic cups in which the soil resided, and we labelled them with the appropriate field id.

First, the soil samples were dried so that the moisture was out of the soil as we wanted to measure the soil organic matter. This was done in an over on * degrees Celsius for 24 hours. Afterward, we weighed the dry soil with the ceramic cups and subtracted it from the empty pot weight to get the dry soil measurement.
Then, the soil was put in a high-heat oven, which heated up for 1 hour to 500 degrees Celsius and then burned at 500 degrees Celsius for 5 more hours to burn off the organic matter. After this, we weighed the soil in the ceramic cups again, and the weight of the pot was subtracted. And then, the soil organic matter data was created by taking the difference between the dry and the burned soils giving the mass percentage of the soil organic matter.

Analysis

Rstudio

The data collected in this study were analysed using R Core Team 2023 (R Core Team 2023. CRAN R version 4.3.0 Available at https://cran.r-project.org/). Multiple analyses were conducted, including non-metric multidimensional scaling (NMDS) (Podani & Schmera, 2011) and PERMANOVA (Zhu, et al., 2020).

NMDS Analysis

NMDS (Non-metric Multidimensional Scaling) analysis is a multivariate ordination technique widely used in ecology to examine similarities and dissimilarities between samples or objects based on multiple variables (Podani & Schmera, 2011). It is particularly useful when dealing with complex datasets where traditional statistical methods may not be sufficient to uncover underlying patterns, which is the case in this research. In the context of the given analysis, NMDS was employed to explore the relationship between various variables and management intensities.

NMDS works by constructing a dissimilarity matrix based on the chosen variables, which measures the dissimilarity between each pair of samples. The dissimilarity matrix is then used to create a multi-dimensional plot, typically in two or three dimensions, representing the samples as points. The distances between the points on the plot reflect the dissimilarity between the corresponding samples in the dissimilarity matrix. The goal of NMDS is to arrange the points on the plot in a way that preserves the original dissimilarities as much as possible.

The analysis was conducted using the "vegan" package in R (Dixon, 2003), and the stress value was used to assess the fit of the model (Dixon, 2003).

The first section of code (Appendix 1) prepares the response dataset for the analysis. It selects columns 1 to 14 from the original dataset d1_a and applies several transformations to some of the variables (square root transformation). Then, it removes some irrelevant columns (date, field, field_Location, round, and bare_cover1 to bare_cover3). The resulting dataset is stored in d_env.

The second section of code applies a Hellinger transformation to the d_env dataset, which normalises the data and reduces the impact of extremes (Borowska, et al., 2015). The resulting dataset is stored in d_hel_env.

The third section of the code performs the NMDS analysis on the transformed data using the metaMDS function from the vegan package. The analysis is performed with three dimensions (k = 3), and the stress value, which measures how well the NMDS configuration preserves the dissimilarities between the samples, is calculated and displayed. A stress value below 0.1 or 0.05 is considered a good fit, while a stress value of 0.2 is suspect and may require increasing the number of dimensions.

The fourth section of code adds the management variable to the original dataset d1 and stores it in the management dataframe. The variable field is recorded into two management levels: "Extensive" for fields 1, 4, and 5, and "Intensive" for fields 21, 22, and 23.

The final section of code creates a plot of the NMDS analysis with the management variable as a factor. The plot function displays the stress value and the ordiplot function creates the NMDS plot, specifying the choices argument as the first and third dimensions, the type argument as "points," and adjusting the size of the points and labels. The orditorp function adds the species labels to the plot, and the ordiellipse function adds ellipses to the plot for each management level with the corresponding colour (red for "Extensive" and blue for "Intensive"). The abline functions add reference lines to the plot for the x- and y-axes.

Permanova

This section presents the analysis conducted to examine the relationship between multiple variables and management using the PERMANOVA (Permutational Multivariate Analysis of Variance) test (Zhu, et al., 2020; Anderson, 2014). The analysis aimed to assess whether there were significant differences in the multivariate composition of the variables based on different management intensities.

To perform the PERMANOVA test, the variables of interest, along with the management field variable, were combined into a response matrix. The response matrix, named "resp," consisted of ten variables related to environmental conditions (d_hel_env) and the management intensity (management$field). The column name of the management intensity variable was changed to "Intensity_cat" for clarity and consistency.

The PERMANOVA analysis was conducted using the adonis2 function from the Vegan package in RStudio. The PERMANOVA test assessed the multivariate composition of the ten environmental variables by comparing them to the management intensity variable (Intensity_cat). The formula used for the analysis was resp[,c(1:10)] ~ resp$Intensity_cat, indicating that the environmental variables were regressed on the management intensity variable. The adonis2 function also specified parameters such as the number of permutations (perm=999) and the option to disable automatic data transformations (autotransform=F), This is due to the Log10 transformation that Adonis uses by default. However, the Hellinger function has already performed a Square Root transformation on the data..

Groundwater vs Peat

First, a new variable named land_use is created based on the values in the field column of the dataset. This variable categorises the land use as either "organic" or "conventional" agricultural production intensity. The assignment is done using the ifelse() function, which checks if the value in the field column is one of the specified values. The resulting land_use variable enables the differentiation between organic and conventional agricultural production intensity land use.

Next, a variable called underwater is created to represent whether the peat is underwater or not. This is determined by comparing the values in the gl (groundwater level) and cl (canal level) columns. If the groundwater level (gl) is less than the canal level (cl), the underwater variable is set to 1, indicating that the peat is not underwater. Otherwise, it is set to 0, indicating that the peat is underwater.

Another binary variable named land_usage which is based on the management intensity is generated based on the land_use variable. If the land_use is "high" the land_usage variable is set to 1, indicating intensive land management. On the other hand, if the land_use is not "high" (i.e., "low"), the land_usage variable is set to 0, indicating extensive land land management.

A plot is then created to visualise the relationship between the peat underwater status (underwater) and CO2 flux (co2fa). The ggplot() function (Wickham, Chang, Wickham, 2016) is used to generate the plot, with co2fa on the x-axis, land_usage on the y-axis, and underwater represented by different colours. The resulting scatter plot provides an overview of the relationship between peat underwater status and CO_2 flux.

The code continues by creating four separate dataframes to represent different combinations of land use and peat underwater status. These data frames capture the combinations of intensive/extensive land use and underwater/not underwater peat conditions. Each data frame is created using the data.frame() function, incorporating relevant columns from the original dataset.

Following the creation of the dataframes, individual plots are generated to explore the relationships within each combination. The plots are created using ggplot() and geom_point(), similar to the previous plot, and they visualise the relationship between CO_2 flux and the respective combinations of land use and peat underwater status.

Finally, the individual plots are arranged in a grid layout using the grid.arrange() function from the gridExtra package. This arrangement allows for easy comparison and analysis of the relationships across the different combinations. The resulting grid of plots is displayed with a common main title for clarity and presentation purposes.

Overall, this code snippet represents a series of data transformations, variable creations, and plot generation to investigate the connections between land use, peat underwater status, and CO_2 flux within the peatland dataset.

Environmental Variables

For the following analysis the code is analysing and comparing different environmental variables (CO_2 flux, soil moisture, penetration resistance, vegetation height, and groundwater level) in relation to land use and location within a field.

To compare the CO_2 flux with land use and location on the field, a box plot is created using the ggplot() function. The x aesthetic is set to the "field" variable, representing different field numbers, while the y aesthetic is set to the "co2f" variable, representing CO_2 flux. The fill aesthetic is mapped to the "lof" variable, which represents the location on the field. The resulting box plot displays the distribution of CO_2 flux for different land uses and locations on the field.

Similarly, boxplots are created for the remaining variables, including soil moisture, penetration resistance, vegetation height, and groundwater level. The code structure for these boxplots is identical to the one used for CO_2 flux, with the appropriate variables assigned to the y aesthetic and labs() function adjusted to reflect the respective variables being plotted.

Finally, the grid.arrange() function is used to arrange the individual boxplots into a grid layout. The boxplots are passed as arguments to grid.arrange(), and the ncol argument is set to 2 to arrange them in two columns. This arrangement allows for a comprehensive comparison of the different environmental variables and their relationships with land use and field location.

This methodology aims to visually explore and analyse the variations in CO_2 flux, soil moisture, penetration resistance, vegetation height, and groundwater level in relation to land use and location within the field. By utilising boxplots, the code provides a concise summary of the distribution and variability of each variable across different land uses and field locations.

Weather Influence

This section presents the analysis conducted to investigate the significance of weather variables on CO2 flux. Weather data were downloaded from the Dutch National Weather service (KNMI from Stavoren within the date range: 01/02/2023 - 30/04/2023, https://www.knmi.nl/nederland-nu/klimatologie/daggegevens). Specifically, the maximum temperature, precipitation, air humidity, and wind speed were examined in relation to the CO2 flux of specific days. The analysis utilised a linear regression model to explore the potential associations between these weather variables and CO2 flux. The weather data used corresponds to the same day as the CO2 flux measurements.

To begin the analysis, the dataset was preprocessed using RStudio. Missing values in the CO2 flux variable were handled by applying the is.na function to identify missing values and replacing them with the corresponding CO2 flux values from a different variable, co2fa. This is done with the mutate() function, if the function found a missing value in the CO2 flux data it would replace it by the data in the average CO2 flux column. The average CO2 flux data was calculated by taking the data from the 7 metre location and the 30 metre location and dividing it by two .This step ensured that the analysis included complete data for the variables of interest.

Scatter plots were then created to visually explore the relationships between the weather variables and CO2 emissions. Four scatter plots were generated: "Temperature vs. CO2 Emissions," "Precipitation vs. CO2 Emissions," "Air Moisture vs. CO2 Emissions," and "Wind Strength vs. CO2 Emissions." Each plot displayed the CO2 flux on the y-axis and one of the weather variables on the x-axis. Additionally, the colour of the data points represented the corresponding land use category.

The scatter plots revealed the distribution and general trends between the weather variables and CO2 flux. They provided a visual understanding of the potential relationships and allowed for initial observations and insights. It should be noted that while the scatter plots present a useful visualisation of the data, they do not provide a quantitative assessment of the significance of the relationships.

Subsequently, a multiple linear regression model (Field, Miles, 2012) was fitted to the data to quantitatively assess the associations between the weather variables (maximum temperature, precipitation, air humidity, and wind speed) and CO2 flux. The lm function in RStudio was used to create the model, with the CO2 flux (co2f) as the dependent variable and the four weather variables as independent variables. The dataset used for modelling was the preprocessed data obtained earlier.

The model summary was then examined to gain insights into the statistical significance of the weather variables. The summary provided information such as the coefficients, standard errors, t-values, and p-values for each independent variable, as well as the overall performance of the model. This information helped determine the individual contributions of the weather variables to the prediction of CO2 flux.

Additionally, a plot of the model was generated to visualise the relationships between the independent variables and the dependent variable. This plot facilitated the interpretation of the regression coefficients and their corresponding confidence intervals. The plot allowed for a visual assessment of the direction and magnitude of the relationships between the weather variables and CO_2 flux.

Finally, a comparison between the predicted CO_2 flux values from the model and the actual CO_2 flux values was conducted. A data frame was created to store the predicted and actual values. A scatter plot, titled "Predicted vs. Actual CO2 Emissions," was generated to visualise the agreement between the predicted and actual values. The plot included data points representing the predicted CO_2 flux on the y-axis and the actual CO_2 flux on the x-axis. Additionally, a red dashed line was included in the plot to represent a perfect prediction, where the predicted and actual values would align.

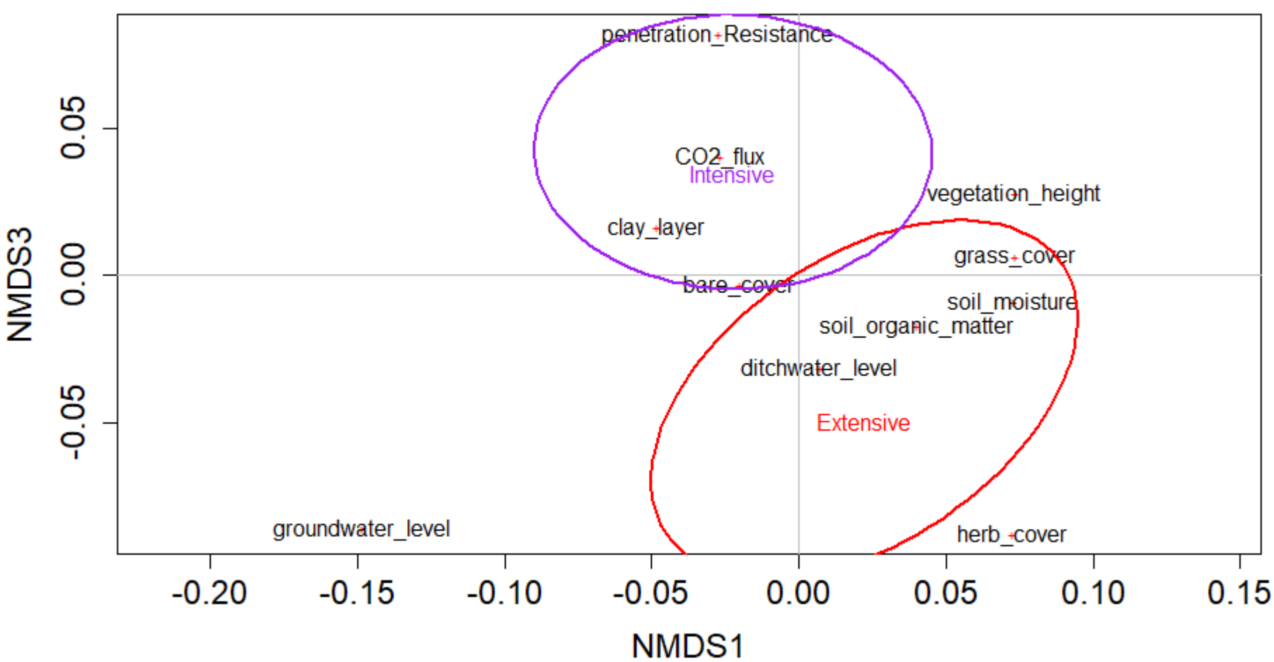
This analysis provides initial insights into the relationships between weather variables and CO_2 flux using a linear regression model. However, it is important to note that the model's performance could potentially be improved by considering a wider range of weather data, including data from multiple days. Furthermore, future research may explore more sophisticated models that can account for additional factors influencing CO_2 flux.

RESULTS

NMDS analysis

The interpretation of an NMDS plot involves examining the spatial arrangement of the points and their relationship to the variables of interest.

The two ellipses in the graph represent the two management intensities, with one ellipse representing more intensive management styles and the other representing extensive management. The ellipses are barely touching each other, indicating a high level of statistical significance and a clear distinction between the management types based on the analysed variables.



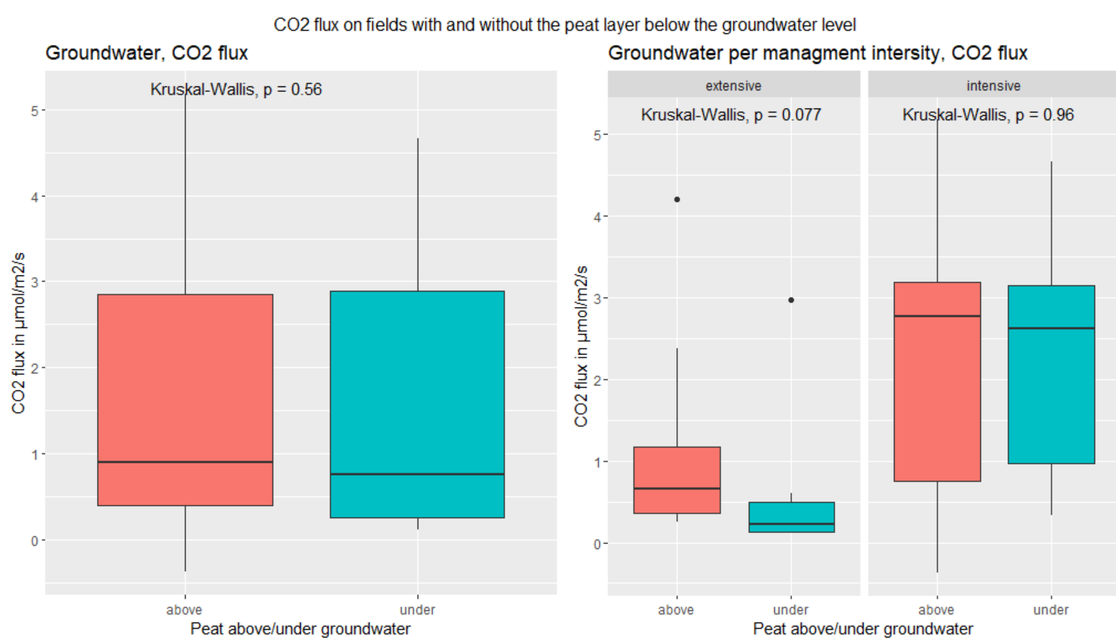
Graph 1 *plot showing NDMS analysis. Ordination is calculated on square root transformed environmental measures. The standard deviation of grouped variables are overlayed as ellipses.*

Thereby, the relative positions of the variables outside or within the ellipses provide insights into their relationship with the management intensities. Variables that fall within the ellipses are more closely associated with the corresponding management style. In contrast, variables outside the ellipses show weaker associations or intermediate characteristics between the two management styles.

According to the figure, higher penetration resistance, higher CO2 flux, deeper peat layer, and more bare ground are more closely related to intensive management. On the other hand, higher ditch water levels, grass cover and soil organic matter and soil moisture are more closely related to extensive management. These variables may be influenced by water management and drainage practices, typically associated with extensive management approaches.

It is important to note that vegetation height is positioned outside the ellipses and closer to the middle. This suggests that these variables do not strongly discriminate between the two management styles, and their values may not be strongly influenced by management practices alone. Groundwater and herb coverage, although also outside the ellipses, are closer to extensive management. These results imply that groundwater levels and herb coverage might be more influenced by factors associated with extensive management practices, such as reduced disturbance and more natural hydrological conditions.

The results indicate that the analysis was run 20 times. The stress values for each run are presented, with additional information regarding the quality of the solutions. In some runs, new best solutions were found, while in others, the solutions were similar to the previous best solution. The Procrustes statistics, such as root mean square error (RMSE) and maximum residual, are also provided. Procrustes analysis is a post-processing step that assesses the fit of the NMDS solution to the original data.



***Graph 2a** peat underwater in correlation to the CO2 flux.* ***2b** peat underwater in correlation to the CO2 flux taking the management intensity into account.*

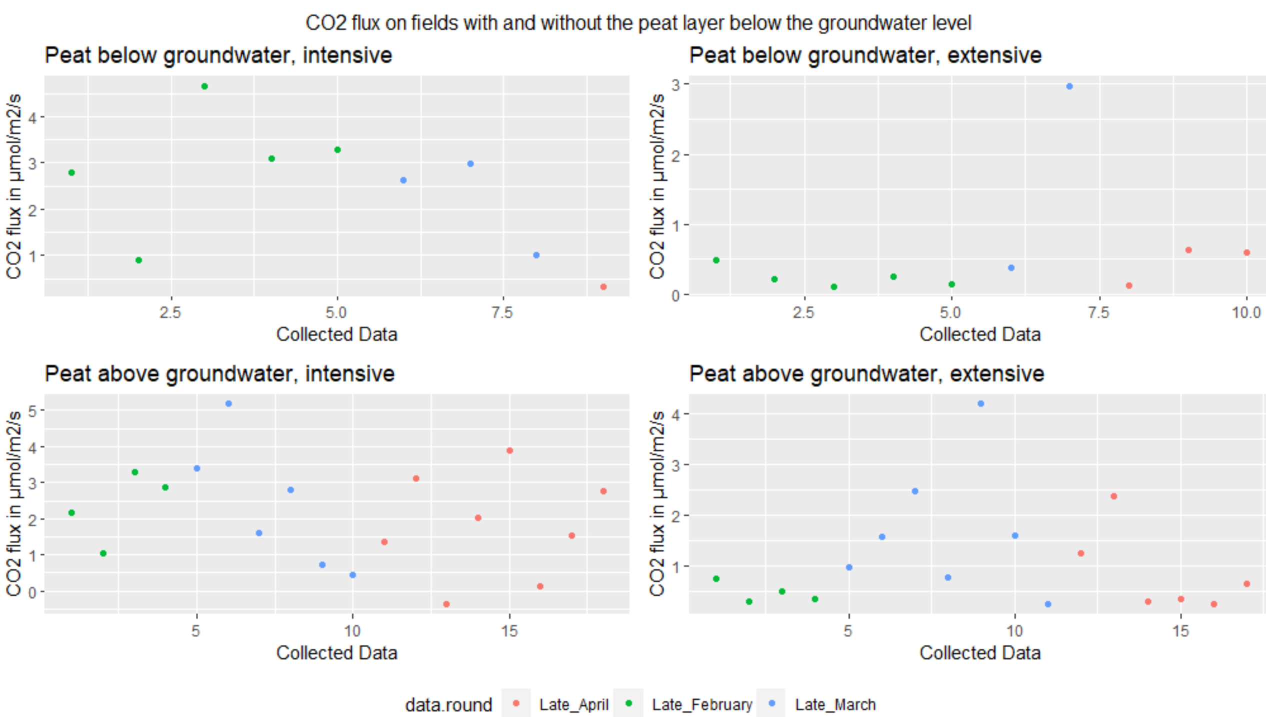
Based on the outcome, the analysis achieved relatively low-stress values in most runs, ranging from 0.1172506 to 0.1284193.

PERMANOVA

The PERMANOVA analysis results revealed a significant effect of management intensity (resp$Intensity_cat) on the multivariate composition of the ten environmental variables (Df = 1, F = 11.63, $p < 0.001$). The environmental variables explained 18.28% of the variation in the composition of the variables ($R^2 = 0.18278$). The remaining 81.72% of the variation was attributed to unexplained factors or random variation within the data (Residual). The total variation in the multivariate composition of the variables accounted for by the model was 100% (Total).

Peat underwater analysis

In order to assess the relationship between CO_2 flux and the presence of groundwater above or under peat soils, statistical analyses were conducted using the Kruskal-Wallis method. The obtained p-value was 0.56, indicating no significant difference in CO_2 flux between fields with groundwater above and under peat soils. However, when further examining the management intensities, the p-values for the extensive and intensive fields were found to be 0.077 and 0.96, respectively. These results suggest that there is a marginal difference in CO_2 flux between fields with groundwater above and under peat soils under extensive management ($p = 0.077$), whereas no significant difference was observed in intensive management ($p = 0.96$). These findings are depicted in Graphs 2a & 2b, which illustrate the correlations between the different fields and management styles with respect to the analysis of peat that is kept underwater.



Graph 3a *plot of the CO2 flux of intensive fields that have their peat underwater.* ***3b*** *plot of the CO2 flux of extensive fields that have their peat underwater.* ***3c*** *plot of the CO2 flux of intensive fields that do not have their peat underwater.* ***3d*** *plot of the CO2 flux of extensive fields that do not have their peat underwater.*

Weather Influence

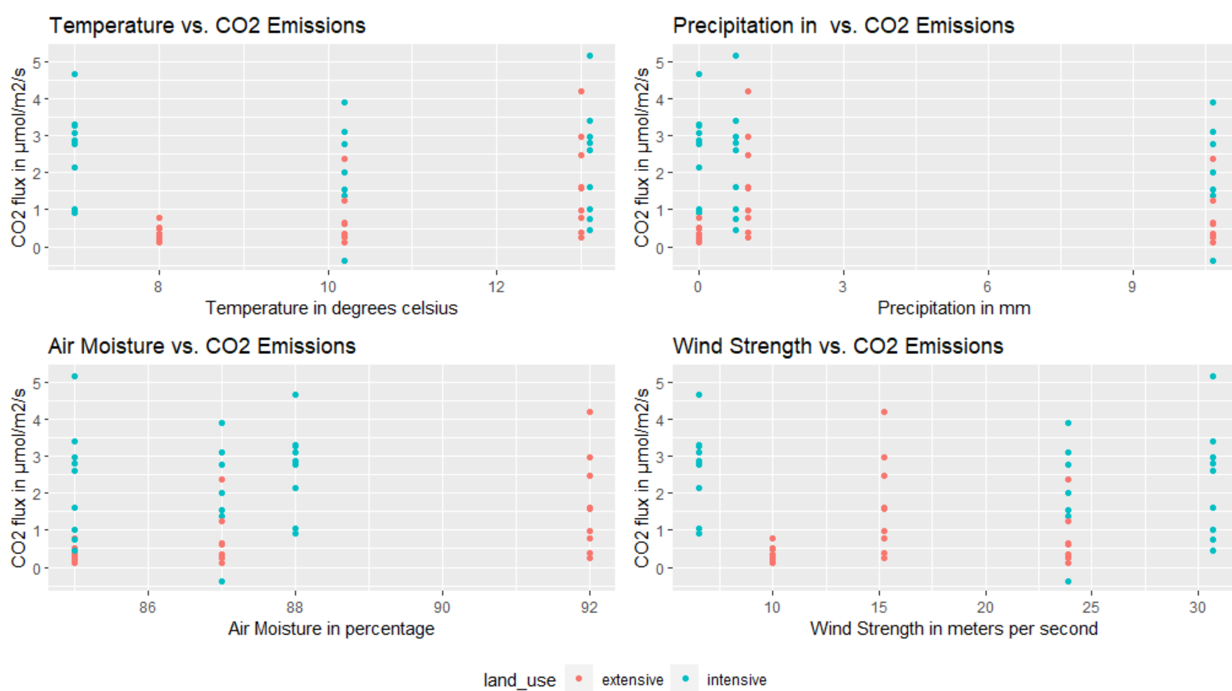
The last analysis was done on the impact of the weather, this is only done with the data of the date of the fieldwork itself and thus for further research, it might be necessary to compile data from the entire week before so that you could have an even more reliable prediction of the influence of the weather on the CO2 emissions.

For the first graphs 4a-d we can see that there is no specific trend in the variables, you could see a trend in the lower intensive fields and the temperature, and the precipitation looks to have a small trend but this is very unclear as the precipitation with 0 and 1 and the co2 precipitation differ a lot.

The results of the regression analysis revealed several important findings. The overall model was found to be significant ($F(4, 49) = 5.8$, $p = 0.0006665$), indicating that the weather variables collectively explain a significant portion of the variance in CO2 flux. The adjusted R-squared value of 0.2659 suggests that approximately 26.59% of the variation in CO2 flux can be accounted for by the weather variables in the model.

Individually, each of the weather variables showed significant relationships with CO2 flux. Maximum temperature (TMAX) was found to have a negative coefficient estimate of -1.27575 ($t = -4.122$, $p = 0.000145$), indicating that higher temperatures are associated with lower CO2 flux. Precipitation (PP) also exhibited a negative relationship, with a coefficient estimate of -0.36715 ($t = -4.633$, $p = 2.68e-05$), suggesting that increased precipitation is associated with decreased CO2 flux.

On the other hand, average air humidity (AVH) showed a positive relationship with CO2 flux, as



***Graph 4a** plot that shows the temperature data in correlation to the CO2 flux and management style. **4b** plot that shows the precipitation data in correlation to the CO2 flux and management style. **4c** plot that shows the air moisture data in correlation to the CO2 flux and management style. **4d** plot that shows the wind speed data in correlation to the CO2 flux and management style.*

indicated by a coefficient estimate of 0.84206 ($t = 4.389$, $p = 6.06e-05$). This implies that higher levels of air humidity correspond to higher CO_2 flux. Similarly, average wind strength (AVW) demonstrated a positive association with CO_2 flux, with a coefficient estimate of 0.42247 ($t = 4.376$, $p = 6.32e-05$). This suggests that stronger wind speeds are linked to higher CO_2 flux.

The model's diagnostic statistics revealed a residual standard error of 1.176, indicating the average magnitude of the residuals. The residuals exhibited a range from -1.85119 to 2.86235, with the majority falling within the first and third quartiles. These statistics provide insights into the model's goodness of fit and the variability of the observed CO_2 flux values around the predicted values.
For further research, these results indicate that an ANCOVA analysis would help to distinguish if there are also differences between management types.

DISCUSSION

The findings of this study offer significant insights into the relationship between management intensities, environmental variables, and peat emissions in peatland ecosystems. By analysing a range of variables and employing multivariate statistical techniques, we can better understand the dynamics and implications of different management practices. Moreover, comparing our results to prior research allows us to identify commonalities and differences, providing a broader context for interpretation.

NMDS analysis

Our NMDS analysis revealed distinct associations between specific variables and management styles. Variables such as penetration resistance, CO_2 flux, peat layer depth, and bare ground were closely linked to intensive management, reflecting the impacts of practices like ploughing and high nutrient input. These practices contribute to soil compaction, increased carbon dioxide emissions, and alterations in peat layer composition. Conversely, variables like ditch water levels, grass cover, soil organic matter, and soil moisture showed stronger associations with extensive management, influenced by water management and drainage practices. These results highlight the influence of management intensity on key environmental variables and the trade-offs associated with different management strategies.

The variables identified in our NMDS analysis reflect the impact of intensive management practices such as ploughing, high nutrient input, and disturbances. These practices lead to increased soil compaction, higher carbon dioxide emissions, and alterations in peat layer composition (Carter & Janzen, 1997).

In comparison to previous NMDS studies, our findings demonstrate both similarities and differences, depending on contextual factors, variables considered, and specific management practices. Discrepancies may arise from variations in management practices, ecological context, or the specific set of variables examined. These discrepancies highlight the significance of considering site-specific factors.

Xu et al. (2020) explored the effects of management intensification on soil properties and microbial communities, finding clear separation between intensive and extensive management. This suggests that the association between management intensities and ecological variables can fluctuate depending on the ecosystem and factors under investigation.

In summary, NMDS analysis is a valuable tool for examining relationships between variables and management intensities. Our analysis shows distinct associations between certain variables and management styles. However, interpretation should consider the study context and incorporate relevant research. NMDS provides insights into the associations between management intensities and ecological variables, contributing to our understanding of the effects of different management strategies.

PERMANOVA

The PERMANOVA analysis revealed a significant effect of management intensity on the overall environmental conditions represented by the variables, indicating that management practices exert a substantial influence on the multivariate composition of soil conditions within the context of this study. These results demonstrate a clear association between management intensity and the studied environmental variables, suggesting that different management practices significantly affect soil conditions. The observed differences in soil conditions can have broader implications for ecosystem functioning and sustainability. For instance, intensive management practices that increase soil compaction and carbon dioxide emissions may contribute to environmental degradation. At a landscape scale, intensive agricultural management can accumulate negative impacts on climate through increased emissions of greenhouse gases. In contrast, extensive management practices that prioritise water management and maintain favourable soil conditions may contribute to biodiversity conservation and carbon sequestration. Therefore, an increased prevalence of lower intensity agricultural production at the landscape scale, as opposed to intensive agricultural production, would yield positive impacts for climate regulation. These findings highlight the need for analysing the environmental implications of different management intensities and promoting sustainable practices that minimise negative impacts.

Peat underwater analysis

The analysis of peat that was being kept under the groundwater level has yielded insightful results, shedding light on the intricate dynamics of CO2 flux in peatland ecosystems.

Upon examining the initial two graphs, which delve into the CO2 flux per management site and the presence of peat underwater, it becomes apparent that the significance of the correlation may not be immediately discernible. Nevertheless, our analysis does reveal intriguing discrepancies in management practices, notably evident in the markedly higher CO2 flux values observed in intensive fields compared to extensive fields. Moreover, when peat is located under the groundwater level, a discernible trend emerges, albeit without a clear indication of statistical significance.

Further research could therefore map the topography of wet/dry peat. As drained peat becomes hydrophobic and requires years of rewetting to restore to a wet state. Wet peat becomes anoxic, which in theory reduces the release of GHG.

In contrast, the subsequent four plots provide a more robust basis for drawing meaningful conclusions. By categorising the variables into four distinct groups—intensive fields with peat underwater, intensive fields without peat underwater, extensive fields with peat underwater, and extensive fields without peat underwater—we gain deeper insights into the interplay between peat conditions, management practices, and CO2 flux dynamics. Notably, the distribution of fields with peat underwater (hereinafter referred to as peun) appears to be relatively balanced between extensive and intensive fields, with only marginal discrepancies in quantity. Furthermore, a careful examination of our data reveals an intriguing temporal aspect, with peun fields being more prevalent during the initial round of fieldwork, while subsequent rounds exhibit a notable decrease in the number of fields with peat underwater.

Delving further into the results, we uncover compelling patterns in CO_2 flux behaviour across different field types. Extensive fields, characterised by more extensive coverage of vegetation and a less intensive management approach, exhibit a higher degree of stability in their CO_2 flux dynamics. Although occasional extremes exist, particularly in non-peun fields where the variables display greater scatter, the overall CO_2 flux values remain relatively consistent. Moreover, compared to intensive fields, extensive fields demonstrate lower CO_2 flux levels, indicating the influence of management practices and groundwater levels on the observed flux patterns. These findings align with prior research conducted by Marwanto et al. (2019), who similarly observed lower CO_2 flux values in peun fields within both intensive and extensive contexts. These corroborating findings support the notion that groundwater levels play a significant role in regulating CO_2 flux in peatland ecosystems.

However, a nuanced analysis of the intensive fields reveals persistent disparities between peun and non-peun fields, even when the groundwater level is above the peat. While CO_2 flux values in peun fields generally exhibit lower magnitudes, it is essential to exercise caution when comparing them directly to the lower flux numbers observed in extensive fields. This observation underscores the complex relationship between groundwater levels, peat conditions, and CO_2 flux dynamics, warranting further investigation. Here, the study by Hoyt, et al. (2019) focuses on reporting contrasting results that suggest a limited influence of peat conditions on CO_2 flux. These divergent findings highlight the site-specific nature of peatland dynamics and the need for comprehensive studies encompassing multiple factors and contexts.
Conditions.

Analysing peat underwater provided valuable insights into CO_2 flux dynamics in peatland ecosystems. Our results showed higher CO_2 flux values in intensive fields compared to extensive fields, indicating the influence of management practices. This finding aligns with prior research and supports the notion that intensive management practices contribute to higher carbon dioxide emissions (Li, Zhou, Wang, 2019). Additionally, the presence of peat underwater showed a discernible trend, although statistical significance was not reached. Extensive fields demonstrated higher stability in CO_2 flux dynamics, with lower overall flux levels than intensive fields. These findings highlight the importance of groundwater levels in regulating CO_2 flux in peatland ecosystems. Adequate rewetting management practices that restore optimal groundwater levels help mitigate carbon dioxide emissions and preserve the integrity of peatland ecosystems (Cui, et al., 2017).

Weather Influence

In this study, the graphs 4a - 4d presented include weather data in relation to CO_2 flux from peat soils. However, it is important to note that the weather data collected solely from the field days itself may not provide a comprehensive view of the overall weather conditions during the entire spring period. This limitation arises from the fact that the graphs do not account for the cumulative effects of weather patterns throughout the spring season.

Furthermore, it should be emphasised that the wettest spring in recent history, as widely reported in the news (KNMI, 2023), has not been explicitly captured in the graphs. The absence of a graph displaying cumulative precipitation for the study period relative to the average hinders a direct assessment of the impact of this notable weather event on groundwater dynamics and CO_2 emissions.

Location

The analysis of variables per field and field location, which can be found in Appendix 2, further revealed trends in CO_2 flux based on management styles and field locations. Extensive fields consistently exhibited lower CO_2 flux, particularly at the 7-metre distance within the field. In contrast, intensive fields demonstrated higher average CO_2 flux but with less variation across field locations. These findings suggest that field locations influence CO_2 flux at different distances. The observed variations in CO_2 flux patterns based on field locations may be attributed to variations in soil characteristics, hydrology, and management practices within the peatland ecosystem. Topography and hydrophobic nature of drained peat might also play a role in these outcomes.

LIMITATIONS

Despite the valuable insights provided by this study, it is important to acknowledge its limitations. Firstly, the study is relatively small and time-limited, which may affect the generalizability of the findings. The trends observed in the data could be enhanced by expanding the sample size and including a more extensive range of fields within each management type. Moreover, the sampling campaign should be extended throughout the entire growing season (March - October) to capture the full dynamics of soil conditions and environmental variables.

Another limitation is the reliance on weekly measurements, which may not fully capture the impact of weather fluctuations on the measured variables. To better understand the influence of weather on the measurements, future studies should consider summing the data per week preceding each measurement to account for weather variations and provide a more accurate representation of environmental conditions.

Furthermore, certain measures, such as vegetation height, are known to be influenced by the position within the growing season. Vegetation growth tends to be slower during the initial stages when the weather is cold and wet, while it accelerates logarithmically as conditions become warmer and drier later in the season. Therefore, the timing of measurements within the growing season can introduce variability in the data, which should be taken into account in future research.

And the last limitation is the unpredictability of other environmental factors. Some examples of these were the mice plaguing the farm fields in the first round and the goose that ate much of the vegetation. Both these biological factors might have had an impact and further research is necessary to determine the significance of these impacts.

Despite these limitations, the findings of this study provide a basis for several policy recommendations aimed at promoting sustainable peatland management. These recommendations include encouraging the adoption of extensive management practices that prioritise water management and maintain favourable soil conditions. Strategies such as controlled drainage systems to maintain optimal groundwater levels, avoiding over-drainage, re-wetting restoration measures and minimising soil compaction can contribute to sustainable peatland management. Additionally, reducing intensive management practices involving ploughing and high nutrient and chemical inputs can help mitigate carbon dioxide emissions and preserve the integrity of peatland ecosystems. To support these recommendations, raising awareness among farmers and landowners about the environmental impacts of different management intensities and providing incentives for sustainable management practices are crucial steps towards achieving positive change in peatland management.

In addition to the aforementioned policy recommendations, addressing the issue of incentives for farmers who already demonstrate effective management practices on peatlands is of paramount importance. Currently, existing incentives tend to be aimed at farmers who possess the potential to "improve" their peatland management approaches. However, it is essential to acknowledge that farmers who already exhibit favourable management practices may not have the capacity to further enhance their strategies in the same manner.

These farmers serve as valuable role models and provide essential demonstration areas for sustainable peatland management. Acknowledging their efforts and providing rewards for their positive contributions can significantly contribute to fostering positive transitions towards sustainable land management. Psychological research emphasises the significance of recognition and intrinsic motivation in promoting desired behaviours (Deci & Ryan, 2000; Ryan & Deci, 2017). By implementing rewards for these farmers, such as financial incentives, recognition programs, or other forms of support, their successful practices can be acknowledged and showcased, thereby stimulating motivation and promoting further adoption of sustainable peatland management practices.

CONCLUSION

In conclusion, this comprehensive study has provided valuable insights into the relationship between management intensities, environmental variables, and peat emissions in peatland ecosystems. The use of NMDS analysis revealed distinct associations between specific variables and management styles, highlighting the impacts of intensive and extensive management practices on key environmental variables. The PERMANOVA analysis further emphasised the significant effect of management intensity on overall soil conditions, indicating that different management practices significantly influence soil conditions in peatland ecosystems. The analysis of peat underwater provided additional insights into CO2 flux dynamics, with higher CO2 flux values observed in intensive fields compared to extensive fields.

The findings of this study demonstrate the importance of considering site-specific factors and tailoring management approaches accordingly. While our results align with previous research in some aspects, such as the lower CO2 flux values observed in extensive fields, discrepancies were also identified, emphasising peatland dynamics' complex and context-dependent nature.

Based on the findings, several policy recommendations can be made to promote sustainable peatland management. Encouraging the adoption of extensive management practices that prioritise water management, minimise soil compaction, and avoid over-drainage is crucial. Implementing controlled drainage systems, re-wetting restoration measures, and reducing intensive management practices can contribute to sustainable peatland management and mitigate carbon dioxide emissions. Raising awareness among farmers and landowners about the environmental impacts of different management intensities and providing incentives for sustainable management practices are essential steps towards achieving positive change in peatland management.

Furthermore, recognising and rewarding farmers who already demonstrate effective management practices on peatlands is paramount. These farmers serve as role models and provide essential demonstration areas for sustainable peatland management. Acknowledging their efforts and providing rewards for their positive contributions can significantly contribute to fostering positive transitions towards sustainable land management.

In conclusion, this study has provided significant insights into the dynamics and implications of different management practices on peatland ecosystems. The findings contribute to our understanding of the complex relationships between management intensities, environmental variables, and peat emissions. By considering site-specific factors, implementing sustainable management practices, and recognising the efforts of farmers, policymakers and land managers can work towards preserving peatland ecosystems, mitigating carbon dioxide emissions, and promoting sustainable land management practices.

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REFERENCES

Anderson, M. J. (2014, April 14). Permutational multivariate analysis of variance (PERMANOVA). Wiley statsref: Statistics Reference Online, 1-5. DOI: 10.1002/9781118445112.stat07841

Archive: Agricultural Census in the Netherlands - Statistics Explained. (n.d.). Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php/Archive:Agricultural_census_in_the_Netherlands

Berendse, F. (2001). Effects of elevated CO2 on nutrient cycling in grazed grasslands. Plant and Soil, 228(2), 229-238. DOI: 10.1023/A:1004809417960

Boer, G. J., et al. (2019). The importance of peatland management for mitigating climate change. Nature, 566(7742), 414-415. DOI: 10.1038/d41586-019-00486-5

Borowska, M., Brzozowska, E., & Oczeretko, E. (2015). The Hilbert Transform in Analysis of Uterine Contraction Activity. Studies in Logic, Grammar and Rhetoric, 42(55), 47-59.

Brown, C., et al. (2021). Impacts of land use and climate change on soil carbon stocks in a tropical rainforest catchment. Geoderma, 405, 115312. DOI: 10.1016/j.geoderma.2021.115312

Carter, M. R., & Janzen, H. H. (1997). Soil sampling and methods of analysis (2nd ed.). Canadian Society of Soil Science, CRC Press.

Chimner, R., & Cooper, D. (2003). Influence of water table levels on CO2 emissions in a Colorado subalpine fen: an in situ microcosm study. Soil Biology & Biochemistry.

Cui, L., Kang, X., Li, W., Hao, Y., Zhang, Y., Wang, J., Yan, L., Zhang, X., Zhang, M., Zhou, J., & Kardol, P. (2017). Rewetting Decreases Carbon Emissions from the Zoige Alpine Peatland on the Tibetan Plateau. Sustainability, 9(9), 1663. DOI: 10.3390/su9091663

Cui, X., et al. (2017). Changes in soil organic carbon and total nitrogen under different land uses in a typical arid area of Northwest China. Environmental Earth Sciences, 76(2), 79. DOI: 10.1007/s12665-016-6329-6

De Mulder, E.F.J. (2019). Water. In: The Netherlands and the Dutch. World Regional Geography Book Series. Springer, Cham. https://doi.org/10.1007/978-3-319-75073-6_2

Deru, J., Bloem, J., Goede, R., Keidel, H., Kloen, H., Rutgers, M., Akker, J., Brussaard, L., & Eekeren, N. (2017). Soil ecology and ecosystem services of dairy and semi-natural grasslands on peat. Applied Soil Ecology.

Dixon, G. R. (2003). The effect of air pollution on crops and amenity plants. Environmental Pollution, 124(2), 233-242. DOI: 10.1016/S0269-7491(02)00475-5

Dixon, P. (2003). VEGAN, a package of R functions for community ecology.

Erkens, G., van der Meulen, M.J. & Middelkoop, H. (2015). Double trouble: subsidence and CO2 respiration due to 1,000 years of Dutch coastal peatlands cultivation. Hydrogeol J 24, 551–568 (2016). https://doi.org/10.1007/s10040-016-1380-4

Field, R., & Miles, J. (2012). Understanding land use and land cover change in Western Europe: A methodology to integrate social and environmental data. Land Use Policy, 29(2), 392-399. DOI: 10.1016/j.landusepol.2011.07.001

Garnier, E., et al. (2004). Plant functional markers capture ecosystem properties during secondary succession. Ecology, 85(9), 2630-2637. DOI: 10.1890/03-0799

Gomez, D. R., et al. (2019). The role of land use in shaping soil bacterial communities in Northeast China. Land Degradation & Development, 30(13), 1543-1555. DOI: 10.1002/ldr.3394

Harenda, Kamila & Lamentowicz, Mariusz & Samson, Mateusz & Chojnicki, Bogdan. (2018). The Role of Peatlands and Their Carbon Storage Function in the Context of Climate Change. 10.1007/978-3-319-71788-3_12.

Havlin, J. L., et al. (2014). Soil fertility and fertilisers: An introduction to nutrient management (8th ed.). Pearson.

Hoyt, A., Gandois, L., Eri, J., Kai, F., Harvey, C., & Cobb, A. (2019). CO2 emissions from an undrained tropical peatland: Interacting influences of temperature, shading and water table depth. Global Change Biology.

IPCC. (2019). Climate change and land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. IPCC.

Jones, D. L., et al. (2009). Nutrient stripping: The global disparity between food security and soil nutrient stocks. Journal of Applied Ecology, 46(4), 831-840. DOI: 10.1111/j.1365-2664.2009.01614.x

KNMI. (2023, June 5). Op een na natste lente van deze eeuw. KNMI. Retrieved from https://www.knmi.nl/over-het-knmi/nieuws/op-een-na-natste-lente-van-deze-eeuw

Kraamwinkel, C (in progress).

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. Science, 304(5677), 1623-1627. DOI: 10.1126/science.1097396

Li, J., et al. (2017). Long-term effects of reclamation on soil organic carbon fractions and stocks in a coastal area of eastern China. Catena, 150, 12-19. DOI: 10.1016/j.catena.2016.10.012

Linden, M., Heijmans, M., & Geel, B. (2014). Carbon accumulation in peat deposits from northern Sweden to northern Germany during the last millennium. The Holocene.

Lorenz, K., et al. (2020). Plant functional traits and soil properties jointly shape community assembly in temperate grasslands. Journal of Ecology, 108(3), 1113-1125. DOI: 10.1111/1365-2745.13343

Marwanto, S., Sabiham, S., & Funakawa, S. (2019). Importance of CO2 production in subsoil layers of drained tropical peatland under mature oil palm plantation. Soil and Tillage Research.

McBratney, A. B., & Pringle, M. J. (1999). Estimating average and proportional variograms of soil properties and their potential use in precision agriculture. Precision Agriculture, 1(2), 125-152. DOI: 10.1023/A:1009990801326

McDowell, R., Cox, N., Daughney, C., Wheeler, D., & Moreau, M. (2015). A National Assessment of the Potential Linkage between Soil, and Surface and Groundwater Concentrations of Phosphorus. JAWRA Journal of the American Water Resources Association.

Moloney, K. A., & Levin, S. A. (1996). The effects of disturbance architecture on landscape-level population dynamics. Ecology Letters, 114(3), 409-423. DOI: 10.2307/2261408

Nannipieri, P., et al. (2003). Soil enzymology: In the last 25 years. Soil Biology and Biochemistry, 35(11), 1453-1456. DOI: 10.1016/j.soilbio.2003.08.001

Navarro-García, F., et al. (2020). Environmental drivers of soil microbial community structure and function at multiple spatial scales in a Mediterranean forest ecosystem. Soil Biology and Biochemistry, 142, 107714. DOI: 10.1016/j.soilbio.2019.107714

Olsen, S. R., et al. (1954). Estimation of available phosphorus in soils by extraction with sodium bicarbonate. United States Department of Agriculture, Circular No. 939.

Page, S. E., & Baird, A. J. (2016). Peatlands and global change: response and resilience. Annual Review of Environment and Resources, 41, 35-57.

Pan, Y., & Wang, X. (2009). Factors controlling the spatial variability of surface soil moisture within revegetated-stabilized desert ecosystems of the Tengger Desert, Northern China. Hydrological Processes.

Pierik, H., Lanen, R., Gouw-Bouman, M., Groenewoudt, B., Wallinga, J., & Hoek, W. (2018). Controls on late-Holocene drift-sand dynamics: The dominant role of human pressure in the Netherlands. The Holocene.

Pons, L.J., 1992. Holocene Peat Formation in the Lower Parts of the Netherlands. In: Verhoeven, J.T.A. (Ed.), Fens and Bogs in the Netherlands: Vegetation, History, Nutrient Dynamics and Conservation. Kluwer Academics Publishers, Dordrecht, the Netherlands

Sánchez-Marañón, M., et al.(2020). Land-use changes drive soil microbial community composition and functional potential in tropical forests. Frontiers in Microbiology, 11, 1727. DOI: 10.3389/fmicb.2020.01727

Schimel, J. P., & Bennett, J. (2004). Nitrogen mineralization: Challenges of a changing paradigm. Ecology, 85(3), 591-602. DOI: 10.1890/03-8002

Shukla, M. K., et al. (2016). Impact of land use change on soil aggregation and aggregate-associated carbon in the Indian Himalayas. Catena, 137, 297-305. DOI: 10.1016/j.catena.2015.10.020

Smith, P., et al. (2016). Biophysical and economic limits to negative CO2 emissions. Nature Climate Change, 6(1), 42-50. DOI: 10.1038/nclimate2870

Stark, J. M., & Firestone, M. K. (1995). Mechanisms for soil moisture effects on activity of nitrifying bacteria. Applied and Environmental Microbiology, 61(1), 218-221. DOI: 10.1128/AEM.61.1.218-221.1995

Stocker, T. F., et al. (2013). Climate change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental

Panel on Climate Change. Cambridge University Press.

Tilman, D., et al. (2001). Global environmental impacts of agricultural expansion: The need for sustainable and efficient practices. Proceedings of the National Academy of Sciences, 98(15), 6709-6714. DOI: 10.1073/pnas.261400498

Vitousek, P. M., et al. (1997). Human alteration of the global nitrogen cycle: Sources and consequences. Ecological Applications, 7(3), 737-750. DOI: 10.1890/1051-0761(1997)007[0737:HAOTGN]2.0.CO;2

Wang, J., et al. (2019). Land-use types and soil chemical properties in karst landscapes of southwestern China. Land Degradation & Development, 30(9), 1082-1093. DOI: 10.1002/ldr.3307

Weil, Raymond & Brady, Nyle. (2017). The Nature and Properties of Soils. 15th edition.

Wu, X., et al. (2018). Effects of land use types on soil organic carbon in the hilly region of the Loess Plateau, China. Journal of Soils and Sediments, 18(9), 2827-2836. DOI: 10.1007/s11368-018-1999-7

Xue, L., Ren, H., Brodribb, T., Wang, J., Yao, X., & Li, S. (2020). Long term effects of management practice intensification on soil microbial community structure and co-occurrence network in a non-timber plantation. Forest Ecology and Management.

Zhang, C., et al. (2020). Effects of land use types on soil properties and microbial community in the central Loess Plateau of China. Ecological Indicators, 108, 105707. DOI: 10.1016/j.ecolind.2019.105707

APPENDIXES

Appendix 1 (CODE)

Capstone Data

2023-01-08

##Reading the data: #The data is extracted using the read.csv command and it uses the file path to get to the data, after that I rename the data in the dataset "CD"

```
data <- read_excel("C:/Users/Eigenaar/Downloads/Analysis_sheet.xlsx")

data$land_use <- ifelse(data$field %in% c(1, 4, 5), "low", "high")
```

Create a new variable for if the peat is underwater using binary (1 if the peat is not underwater, 0 if the peat is underwater)

```
data$underwater <- ifelse(data$gl<data$cl, 1, 0)
```

Plot if the land_usage is intensive or not by ussing binary (1 for high, 0 for low intensity)

```
data$land_usage <- ifelse(data$land_use=="high", 1, 0)
```

Create a plot showing the Peat underwater in correlation to the CO2 flux

```
ggplot(data,
       aes(x =co2fa, y=land_usage, col=underwater)) +
  labs(title = "Peat underwater and CO2 flux") +
  geom_point(alpha=0.5)
```

Make dataframes for the four possibilities

```
underwater_intensive <- data.frame(data$land_usage == 1 & data$underwater ==
0, data$co2f, data$co2fa, data$round)

underwater_extensive <- data.frame(data$land_usage == 0 & data$underwater ==
0, data$co2f, data$co2fa, data$round)

notunderwater_intensive <- data.frame(data$land_usage == 1 & data$underwater
== 1, data$co2f, data$co2fa, data$round)

notunderwater_extensive <- data.frame(data$land_usage == 0 & data$underwater
== 1, data$co2f, data$co2fa, data$round)
```

#Plot the 4 possibilities

```
underwater_intensive <- underwater_intensive %>%
  mutate(co2f_a =
           data.co2f %>%
             is.na %>%
             ifelse(data.co2fa, data.co2f) )
unin <-
underwater_intensive[underwater_intensive$data.land_usage....1...data.underwa
ter....0 != "FALSE", ]
uninplot <- ggplot(unin, aes(x=c(1:9) ,y = co2f_a, color = data.round)) +
   geom_point() +
  labs(title = "Intensive field, Peat underwater Co2f", x = "Intensive and
Peat underwater", y = "Co2 flux")

underwater_extensive <- underwater_extensive %>%
  mutate(co2f_a =
           data.co2f %>%
             is.na %>%
             ifelse(data.co2fa, data.co2f) )
unex <-
underwater_extensive[underwater_extensive$data.land_usage....0...data.underwa
ter....0 != "FALSE", ]
unexplot <- ggplot(unex, aes(x=c(1:10) ,y = co2f_a, color = data.round)) +
   geom_point() +
  labs(title = "Extensive field, Peat underwater Co2f", x = "Extensive and
Peat underwater", y = "Co2 flux")


notunderwater_intensive <- notunderwater_intensive %>%
  mutate(co2f_a =
           data.co2f %>%
             is.na %>%
             ifelse(data.co2fa, data.co2f) )
noin <-
notunderwater_intensive[notunderwater_intensive$data.land_usage....1...data.u
nderwater....1 != "FALSE", ]
```

```
noinplot <- ggplot(noin, aes(x=c(1:18) ,y = co2f_a, color = data.round)) +
   geom_point() +
  labs(title = "Intensive field, Peat not underwater Co2f", x = "Intensive
and Peat not underwater", y = "Co2 flux")

notunderwater_extensive <- notunderwater_extensive %>%
  mutate(co2f_a =
           data.co2f %>%
             is.na %>%
             ifelse(data.co2fa, data.co2f) )
noex <-
notunderwater_extensive[notunderwater_extensive$data.land_usage....0...data.u
nderwater....1 != "FALSE", ]
noexplot <- ggplot(noex, aes(x=c(1:17) ,y = co2f_a, color = data.round)) +
   geom_point() +
  labs(title = "Extensive field, Peat not underwater Co2f", x = "Extensive
and Peat not underwater", y = "Co2 flux")
grid.arrange(uninplot, unexplot, noinplot, noexplot, ncol = 2, top="Main
Title")
```

Separate the data by land use

```
high_intensity <- data %>% filter(field %in% c(21, 22, 23))
low_intensity <- data %>% filter(field %in% c(1, 4, 5))
```

Create summary statistics for each field

```
high_summary <- high_intensity %>% group_by(lof) %>%
  summarise(mean_co2f <- mean(co2f, na.rm = TRUE),
            mean_gl = mean(gl),
            mean_dl = mean(dl),
            mean_pra = mean(pra),
            mean_sma = mean(sma),
            mean_vha = mean(vha),
            mean_pgrass = mean(pgrass),
```

```
            mean_pherbs = mean(pherbs),
            mean_bare = mean(pbare),
            mean_SOM <- mean(SOM, na.rm = TRUE))

low_summary <- low_intensity %>% group_by(lof) %>%
  summarise(mean_co2f <- mean(co2f, na.rm = TRUE),
            mean_gl = mean(gl),
            mean_dl = mean(dl),
            mean_pra = mean(pra),
            mean_sma = mean(sma),
            mean_vha = mean(vha),
            mean_pgrass = mean(pgrass),
            mean_pherbs = mean(pherbs),
            mean_bare = mean(pbare),
            mean_SOM <- mean(SOM, na.rm = TRUE))

high_summary

##   mean_co2f <- mean(co2f, na.rm = TRUE)  mean_gl  mean_dl mean_pra
mean_sma
## 1                              2.209119 51.59259 46.11111 92.06173
60.15926
##   mean_vha mean_pgrass mean_pherbs mean_bare
## 1 9.834568    81.88889    7.222222  10.88889
##   mean_SOM <- mean(SOM, na.rm = TRUE)
## 1                            4.612778

low_summary

##   mean_co2f <- mean(co2f, na.rm = TRUE)  mean_gl  mean_dl mean_pra
mean_sma
## 1                             0.9234044 38.25926 43.33333 78.23457
65.78765
##   mean_vha mean_pgrass mean_pherbs mean_bare
## 1 8.190123    57.38889     37.2037  5.407407
##   mean_SOM <- mean(SOM, na.rm = TRUE)
## 1                            4.728889
```

Compare groundwater level to peat depth by land use

```
high_plot <- ggplot(high_intensity, aes(x = cl, y = gl)) +
  geom_point() +
  geom_smooth(method = "lm") +
  labs(title = "High Intensity Land Use", x = "Peat Depth (cm)", y =
"Groundwater Level (cm)")

low_plot <- ggplot(low_intensity, aes(x = cl, y = gl)) +
  geom_point() +
  geom_smooth(method = "lm") +
  labs(title = "Low Intensity Land Use", x = "Peat Depth (cm)", y =
```

```
"Groundwater Level (cm)")

grid.arrange(high_plot, low_plot, ncol = 2)

## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```

Compare co2 flux to land use and location on field

```
co2_plot <- ggplot(data, aes(x = factor(field), y = co2f, fill =
factor(lof))) +
  geom_boxplot() +
  facet_wrap(~ lof, ncol = 3) +
  labs(title = "Co2 Flux by Land Use and Location on Field", x = "Field
Number", y = "Co2 Flux")
```

Compare soil moisture to land use and location on field

```
sm_plot <- ggplot(data, aes(x = factor(field), y = sma, fill = factor(lof)))
+
  geom_boxplot() +
  facet_wrap(~ lof, ncol = 3) +
  labs(title = "Soil Moisture by Land Use and Location on Field", x = "Field
Number", y = "Soil Moisture")
```

Compare penetration resistance to land use and location on field

```
pr_plot <- ggplot(data, aes(x = factor(field), y = pra, fill = factor(lof)))
+
  geom_boxplot() +
  facet_wrap(~ lof, ncol = 3) +
  labs(title = "Penetration Resistance by Land Use and Location on Field", x
= "Field Number", y = "Penetration Resistance")
```

Compare vegetation height to land use and location on field

```
vh_plot <- ggplot(data, aes(x = factor(field), y = vha, fill = factor(lof)))
+
  geom_boxplot() +
  facet_wrap(~ lof, ncol = 3) +
  labs(title = "Vegetation Height by Land Use and Location on Field", x =
"Field Number", y = "Vegetation Height")
```

Compare ground water level to land use and location on field

```
gl_plot <- ggplot(data, aes(x = factor(field), y = gl, fill = factor(lof))) +
  geom_boxplot() +
  facet_wrap(~ lof, ncol = 3) +
  labs(title = "Ground Water by Land Use and Location on Field", x = "Field
Number", y = "Groundwater depth")

grid.arrange(co2_plot, gl_plot, vh_plot, sm_plot, pr_plot, ncol = 2)

## Warning: Removed 18 rows containing non-finite values (`stat_boxplot()`).
```

#NMDS Analysis of the dataset

Extract dataset again

```
d1 <- read_excel("C:/Users/Eigenaar/Downloads/Analysis_sheet.xlsx") %>%
  as_tibble() %>%
  select(-c(vh1, vh2, vh3, pr1, pr2, pr3, sm1, sm2, sm3, co2f, SOM, AVH, AVW,
TMAX, PP))
```

Change names if necessary

```
str(d1)

## tibble [54 × 15] (S3: tbl_df/tbl/data.frame)
##  $ field : num [1:54] 21 21 21 22 22 22 23 23 23 1 ...
##  $ date  : POSIXct[1:54], format: "2023-02-28" "2023-02-28" ...
##  $ round : num [1:54] 1 1 1 1 1 1 1 1 1 1 ...
##  $ lof   : num [1:54] 2 7 30 2 7 30 2 7 30 2 ...
```

```
##  $ dl    : num [1:54] 55 55 55 56 56 56 58 58 58 44 ...
##  $ gl    : num [1:54] 64 68 56 64 67 37 78 94 64 42 ...
##  $ cl    : num [1:54] 42 64 34 64.5 70 39 68 117 59 40.5 ...
##  $ sma   : num [1:54] 66.9 52.7 60.6 65.2 54.7 ...
##  $ pra   : num [1:54] 127.3 116 45.3 98 86.7 ...
##  $ vha   : num [1:54] 3.83 4.5 4.43 4.67 5.33 ...
##  $ pgrass: num [1:54] 80 60 70 70 58 76 97 94 94 56 ...
##  $ pherbs: num [1:54] 0 0 14 6 18 8 3 6 6 36 ...
##  $ pbare : num [1:54] 20 40 16 24 24 16 0 0 0 8 ...
##  $ co2fa : num [1:54] 2.78 2.78 2.78 2.15 2.15 ...
##  $ SOMA  : num [1:54] 5.11 5.11 5.11 4.39 4.39 ...
```

```
names(d1)
```

```
##  [1] "field"  "date"   "round"  "lof"    "dl"     "gl"     "cl"     "sma"
##  [9] "pra"    "vha"    "pgrass" "pherbs" "pbare"  "co2fa"  "SOMA"
```

```
d1_a <- d1 %>%
  rename(c("vha"= "veg_height",
           "pgrass"= "grass_cover" ,
           "pherbs" = "herb_cover",
           "pbare" = "bare_cover",
           "co2fa" = "CO2_flux",
           "gl" = "gw_level",
           "sma" = "soil_moisture" ,
           "pra" = "penetration_Resistance",
           "lof" = "field_Location",
           "dl" = "dw_level",
           "cl" = "clay_layer",
           "SOMA" = "Soil_Organic_Matter"))

# prepare response dataset
d_env <- d1_a %>%
  select(c(1:15)) %>%
  mutate(herb_cover = sqrt(herb_cover)) %>%
  mutate(bare_cover1 = sqrt(bare_cover)) %>%
  mutate(bare_cover2 = sqrt(bare_cover1)) %>%
  mutate(bare_cover3 = sqrt(bare_cover2)) %>%
  mutate(bare_cover = sqrt(bare_cover2)) %>%
  mutate(veg_height = sqrt(veg_height)) %>%
    select(-c("date", "field", "field_Location","round", "bare_cover1",
"bare_cover2", "bare_cover3"))

d_hel_env <- decostand(d_env, method="hellinger", na.rm = T)
colnames(d_hel_env)
```

```
##  [1] "dw_level"                "gw_level"               "clay_layer"
##  [4] "soil_moisture"           "penetration_Resistance" "veg_height"
##  [7] "grass_cover"             "herb_cover"             "bare_cover"
## [10] "CO2_flux"                "Soil_Organic_Matter"
```

NMDS environmental

stress of 0.1 or 0.05 and below is a good fit

stress of 0.2 is suspect and should increase number of dimensions

```
nmds1 <- metaMDS(d_hel_env, autotransform = F, k = 3, na.rm = T)

## Run 0 stress 0.1172508
## Run 1 stress 0.121928
## Run 2 stress 0.1292861
## Run 3 stress 0.117701
## ... Procrustes: rmse 0.03302183  max resid 0.1768279
## Run 4 stress 0.1177005
## ... Procrustes: rmse 0.03273792  max resid 0.1766054
## Run 5 stress 0.1221184
## Run 6 stress 0.1177007
## ... Procrustes: rmse 0.03300281  max resid 0.1768111
## Run 7 stress 0.1177
## ... Procrustes: rmse 0.03281504  max resid 0.1764876
## Run 8 stress 0.1272519
## Run 9 stress 0.1172509
## ... Procrustes: rmse 0.0004547197  max resid 0.001844197
## ... Similar to previous best
## Run 10 stress 0.1284192
## Run 11 stress 0.1192616
## Run 12 stress 0.1245222
## Run 13 stress 0.1177004
## ... Procrustes: rmse 0.03295428  max resid 0.1767316
## Run 14 stress 0.1172506
## ... New best solution
## ... Procrustes: rmse 0.0003382292  max resid 0.001416087
## ... Similar to previous best
## Run 15 stress 0.1177001
## ... Procrustes: rmse 0.03298984  max resid 0.1768525
## Run 16 stress 0.1272008
## Run 17 stress 0.1239198
## Run 18 stress 0.1172507
## ... Procrustes: rmse 5.026758e-05  max resid 0.0001652619
## ... Similar to previous best
## Run 19 stress 0.1172507
## ... Procrustes: rmse 0.0002562036  max resid 0.001210745
## ... Similar to previous best
## Run 20 stress 0.1284196
## *** Best solution repeated 3 times
```

```
# default autotransformation not needed when data are already transformed
nmds1    # stress is 0.0986

##
## Call:
## metaMDS(comm = d_hel_env, k = 3, autotransform = F, na.rm = T)
##
## global Multidimensional Scaling using monoMDS
##
## Data:     d_hel_env
## Distance: bray
##
## Dimensions: 3
## Stress:     0.1172506
## Stress type 1, weak ties
## Best solution was repeated 3 times in 20 tries
## The best solution was from try 14 (random start)
## Scaling: centring, PC rotation, halfchange scaling
## Species: expanded scores based on 'd_hel_env'
```

add management

```
management <- d1 %>%
  select("field") %>%
  mutate(field = case_when(field == 1 ~ "Extensive", field == 4 ~
"Extensive", field == 5 ~ "Extensive", field == 21 ~ "Intensive", field == 22
~ "Intensive", field == 23 ~ "Intensive"))

plot(nmds1)
```

```
par(mar=c(5,5,1,1))
ordiplot(nmds1,disp="species",choices=c(1,3),type="points",cex=0.65,cex.axis=
1.5,cex.lab=1.5)
orditorp(nmds1,disp="species",choices=c(1,3),cex=0.65,cex.axis=1.5,cex.lab=1.
5,pcex=0,air=0.01)
abline(v=0, col="grey")
```

```
abline(h=0, col="grey")

colours <- c("red", "purple", "blue", "green")
ordiellipse(nmds1,management$field,label=T,
            col=unique(colours), lwd = 2.5)
```

```
install_github("pmartinezarbizu/pairwiseAdonis/pairwiseAdonis")

## WARNING: Rtools is required to build R packages, but is not currently
installed.
##
## Please download and install Rtools 4.2 from
https://cran.r-project.org/bin/windows/Rtools/ or
https://www.r-project.org/nosvn/winutf8/ucrt3/.

## Skipping install of 'pairwiseAdonis' from a github remote, the SHA1
(68468fe1) has not changed since last install.
##   Use `force = TRUE` to force installation

resp <- cbind(d_hel_env,management$field)
colnames(resp)[11] <- "Intensity_cat"
```

PERMANOVA from package Vegan

```
permanova <- adonis2(resp[,c(1:10)] ~ resp$Intensity_cat, data=resp,
perm=999,autotransform=F,)
permanova

## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## adonis2(formula = resp[, c(1:10)] ~ resp$Intensity_cat, data = resp,
permutations = 999, autotransform = F)
##                     Df SumOfSqs      R2      F Pr(>F)
```

```
## resp$Intensity_cat  1 0.049304 0.18278 11.63  0.001 ***
## Residual           52 0.220444 0.81722
## Total              53 0.269748 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

#Climate Data High & Low

```
dataw <- data %>%
  mutate(co2f =
           co2f %>%
             is.na %>%
             ifelse(co2fa, co2f))

# Scatter plot: Temperature vs. CO2 Emissions
temperature_plot <- ggplot(dataw, aes(x = TMAX, y = co2f, color = land_use))
+
  geom_point() +
  labs(title = "Temperature vs. CO2 Emissions", x = "Temperature", y = "CO2
Flux")

# Scatter plot: Precipitation vs. CO2 Emissions
precipitation_plot <- ggplot(dataw, aes(x = PP, y = co2f, color = land_use))
+
  geom_point() +
  labs(title = "Precipitation vs. CO2 Emissions", x = "Precipitation", y =
"CO2 Flux")

# Scatter plot: Air Moisture vs. CO2 Emissions
air_moisture_plot <- ggplot(dataw, aes(x = AVH, y = co2f, color = land_use))
+
  geom_point() +
  labs(title = "Air Moisture vs. CO2 Emissions", x = "Air Moisture", y = "CO2
Flux")

# Scatter plot: Wind Strength vs. CO2 Emissions
wind_strength_plot <- ggplot(dataw, aes(x = AVW, y = co2f, color = land_use))
+
  geom_point() +
  labs(title = "Wind Strength vs. CO2 Emissions", x = "Wind Strength", y =
"CO2 Flux")

# Combine the plots
grid.arrange(temperature_plot, precipitation_plot, air_moisture_plot,
wind_strength_plot, ncol = 2)
```

```r
# Fit the multiple linear regression model
model <- lm(co2f ~ TMAX + PP + AVH + AVW, data = dataw)

# Check the model summary
summary(model)
```

```
##
## Call:
## lm(formula = co2f ~ TMAX + PP + AVH + AVW, data = dataw)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.85119 -0.84728 -0.05928  0.57413  2.86235
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -65.24218   15.22971  -4.284 8.55e-05 ***
## TMAX         -1.27575    0.30953  -4.122 0.000145 ***
## PP           -0.36715    0.07924  -4.633 2.68e-05 ***
## AVH           0.84206    0.19188   4.389 6.06e-05 ***
## AVW           0.42247    0.09654   4.376 6.32e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.176 on 49 degrees of freedom
## Multiple R-squared:  0.3213, Adjusted R-squared:  0.2659
## F-statistic:   5.8 on 4 and 49 DF,  p-value: 0.0006665
```

```r
plot(model)
```

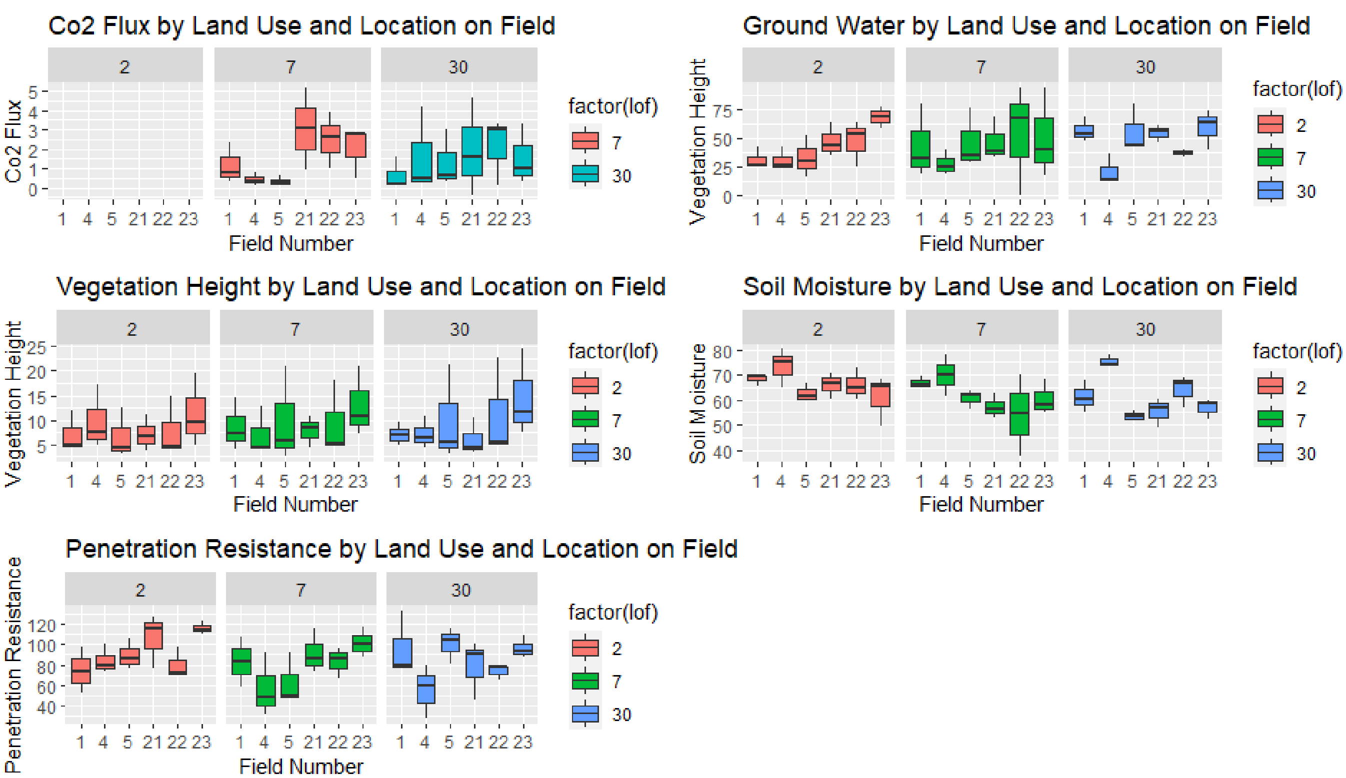
```
# Create a data frame with the predicted CO2 emissions and actual CO2
emissions
predictions <- data.frame(Predicted = predict(model), Actual = data$co2f)

# Scatter plot: Predicted vs. Actual CO2 Emissions
plot <- ggplot(predictions, aes(x = Actual, y = Predicted)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, color = "red", linetype = "dashed") +
  labs(title = "Predicted vs. Actual CO2 Emissions", x = "Actual CO2
Emissions", y = "Predicted CO2 Emissions")

# Display the plot
print(plot)

## Warning: Removed 18 rows containing missing values (`geom_point()`).
```

Appendix 2 (Variables per field and location on the field)

The analysis of multiple environmental variables in correlation with the fields and their locations has provided valuable insights into the relationship between management styles and various factors.

Examining the first graph 6a, which illustrates CO2 flux by field and field location, we observe a trend that aligns with our earlier discussions. Specifically, extensive fields (fields 1, 4, and 5) consistently exhibit lower CO2 flux, particularly at the 7-meter distance within the field. However, the disparity diminishes at the 30-meter distance, where CO2 flux levels tend to be slightly higher. In contrast, intensive fields demonstrate higher average CO2 flux, but the variation across field locations is less pronounced, and interestingly, at the 30-meter region, the fluxes are even slightly lower than at the 7-meter mark. These findings suggest that the field locations play a role in influencing the CO2 flux at different distances. This observation aligns with previous studies by Brown et al. (2021), who reported similar variations in CO2 flux patterns based on field location and management styles, corroborating our findings.

Moving on to the second graph 6b, which depicts groundwater levels by field and field position, the boxplots provide insights into the variations in groundwater across the different field types. In most cases, extensive fields exhibit higher groundwater levels, particularly at the 2-meter distance from the ditch. At the 7-meter mark, the groundwater levels remain relatively consistent across both intensive and extensive fields, while at the 30-meter distance, there is more variability, evident in both management styles. These findings align with



Graph 6a boxplots per field per location of the 3 measurement periods of the CO2 flux variable. 6b boxplots per field per location of the 3 measurement periods of the groundwater variable. 6c boxplots per field per location of the 3 measurement periods of the vegetation height variable. 6d boxplots per field per location of the 3 measurement periods of the soil moisture variable. 6e boxplots per field per location of the 3 measurement periods of the penetration resistance variable.

prior research conducted by Mdowell et al. (2015), who similarly identified differences in groundwater levels between intensive and extensive fields, lending further support to our observations.

Analyzing the third graph 6c, which showcases vegetation height by field and field position, we initially expected to find higher vegetation heights in intensive fields. However, the boxplots reveal that vegetation heights are largely similar across most field types, with only field number 23 exhibiting significantly higher vegetation height. This unexpected result deviates from the anticipated pattern and highlights the complex dynamics at play. While our findings contradict the initial expectation, they do align with the study conducted by Brown et al. (2021), who also observed similarities in vegetation height across various management styles, emphasizing the importance of considering multiple factors when analyzing peatland ecosystems.

Shifting our focus to the fourth graph 6d, which illustrates soil moisture by field and field position, the boxplots demonstrate relatively smaller variations in soil moisture, except for field number 22 at the 7-meter distance from the ditch, where an extreme outlier is observed. Overall, extensive fields exhibit greater variability in soil moisture across different field locations. These observations align with prior research conducted by Pan and Wang (2009), who reported similar trends in soil moisture variations in extensive fields, providing additional support to our findings.

Lastly, the fifth graph 6e, displaying penetration resistance by field and field position, reveals that extensive fields generally exhibit lower penetration resistance, while intensive fields tend to have higher resistance. This finding aligns with existing knowledge regarding the influence of management practices on soil compaction. Studies by Brown et al. (2021) have consistently reported higher penetration resistance in intensive fields, confirming our observations and emphasizing the impact of management styles on soil.