CARBON SEQUESTRATION IN YOUNG TEMPERATE FOOD FORESTS

Bram Antonius Gerardus Wendel

Thesis MSc Industrial Ecology
Faculty of Science - Leiden University and Delft University of Technology
Date: 18 – 6 - 2021
Student numbers: S2671565
First supervisor: Dr. M.J.J. Schrama
Second supervisor: Dr. L.A. Scherer

Acknowledgements

First of all, I would like to thank my first supervisor, Dr M.J.J. Schrama, whose passion and expertise regarding food forests helped me throughout the project. In addition, his enthusiasm and motivation brought my thesis to the next level. Also, I would like to thank my second supervisor Dr L.A. Scherer, who gave thoughtful feedback during the key meetings of the project.

Furthermore, I would like to thank Isabelle der Zanden and Ciska van der Veen of the Netherlands Institute of Ecology (NIOO). Without this collaboration, I was not able to measure the GHG fluxes. Additionally, I would like to thank Peter van Rossum (farmer). He was so helpful and interested to let me enter and analyse his grassland. Also, a valuable collaboration with the National Monitoring Program of Food Forests (NMPFF) was established. I would like to thank Bastiaan Rooduijn (NMPFF), for his profound expertise concerning the carbon measurements in food forests. He gave thoughtful feedback, which improved the approach of this project.

Additionally, throughout this research, I consulted various experts, who were all willing to help. Therefore, I would like to thank Kaspar Buinink (Utrecht University), Morgane van Dam, Heleen Klinkert Vadalkar (Nieuw Groen), Rolf Tonckens, Nico van Eeden, Jan-Willem Erisman (Leiden University), Dirk-Jan Kok (Leiden University), Waas Thissen (ReNature), Marit Kreikamp (University of Amsterdam), Ceriel Lucker (Leiden University), Tijn Tjoelker (ClimateCleanUp), Hendriks Kees (WUR), Fabrice Ottburg (WUR), and Piet Rombouts for offering their expertise and time to guide me.

Finally, I would like to thank Stan de Wit, Chantal Blom (Leiden University), and Esther Rublack (Leiden University) for proofreading this thesis and Irma Laponder (Delft University) for improving my English writing.

Abstract

The food sector plays a crucial role in exceeding several planetary boundaries. Currently, humanity has the challenge to stay between these boundaries. Food forests are an approach for improving ecosystems in soil quality, sequestering carbon and enhancing biodiversity while providing food. However, this concept is yet nearly unstudied in temperate regions. Accordingly, this study attempted to investigate aboveground and belowground storage, carbon fluxes, and the build-up rate in the transition from grassland to a food forest through an in-depth case study in a temperate region. In order to analyse all key carbon pools, a plotless method was applied for the coppice, hedgerows, fruit and nut-bearing trees, and a plot-based method for the grass, herbs, litter and soil organic carbon (SOC).

Overall, the results showed exponential growth in aboveground carbon in the living biomass, though remarkably different patterns for SOC over the first 5.5 years. The ground layer (e.g. grass, herbs, and litter) is a significant source of aboveground carbon in young food forests (95% in year 3.5 to 36% in year 5.5). The trees compartments showed an exponential increase, and the total stored carbon biomass in the food forests at the age of 5.5 is 6.0 $t\ C\ ha^{-1}$. The SOC differed over the years, which is 115 $t\ C\ ha^{-1}$in the grassland and depicts 78 to 136 $t\ C\ ha^{-1}$in year 5.5. Finally, the food forest has the potential to sequester around 4.4 $t\ C\ ha^{-1}\ yr^{-1}$ in above and belowground biomass, functioning as active carbon sinks already within the first five years of the case study. Coppice and hedgerows have proven to be vital in sequestering carbon in living biomass. Further research should investigate older food forests in temperate regions while bearing in mind the potential of coppices and hedgerows. In addition, a better understanding of belowground carbon is essential for assessing the net carbon impact of carbon farming initiatives, as the soil stores most of the carbon.

Keywords: *Food forests, Agroforestry, Carbon stock, Carbon sequestration, Carbon emissions*

Table of Contents

Introduction

Globally, humanity is drastically exceeding the planetary boundaries, in which the food sector plays a crucial role (Björklund, Eksvärd & Schaffer, 2019). Especially boundaries such as climate change, land-use change, biodiversity loss, and disruption in nitrogen cycles are important stressors caused by agricultural practices (Foley, 2011). Additionally, the carbon sequestration potential of the ecosystem reduces globally due to deforestation (Malhi et al., 1999). Carbon sequestration is the mechanism of capturing atmospheric carbon, an important tool to reduce net CO_2 emissions. The transition towards a sustainable food system requires diet changes, declines in food waste, more climate resistance and sustainable food production (Björklund et al., 2019). Altogether, the ambition must be for the agricultural sector to decrease impacts until it becomes carbon negative by shifting towards a circular system and while providing healthy food for all.

This challenge is addressed by agroforestry which integrates food production with improving ecosystems, soil quality and biodiversity (Torralba, Fagerholm, Burgess, Moreno & Plieninger, 2016). These systems propose a nature-inclusive agricultural system by practising agriculture with the inclusion of trees (den Herder et al., 2017). Various combinations of agroforestry have been developed, of which food forests gets increasingly interesting in temperate regions (European Commission, 2021). In this system multiple trees and crops are combined. The necessity of combining environmental values and production increases the opportunity for food forests. Consequently, this approach may even increase the land's productivity because of the combination of trees and other crops in the understory (Torralba et al., 2016). In tropical regions, this is especially evident, where the heterogeneity in the system can enhance productivity (Pandey, Agrawal, & Pandey, 2011), yet more evidence from the temperate areas is needed to support this claim. Furthermore, these food forests regard a way to strengthen ecosystem services, which improves climate change mitigating and adaptation (Toensmeier, 2016).

The carbon sequestration potential is one of the ecosystem services that can help to address climate change, as food forests can be regarded as a type of carbon farming (Toensmeier, 2016). This is a unique form of agriculture because of the inclusion of perennial crops, functioning as a net carbon sink, contrary to traditional agriculture (Montagnini & Nair, 2004). Recently, the European Commission highlighted carbon farming as a key tool for reaching the EU climate targets (COWI & European Commision, 2021). Therefore, valuing the carbon uptake of a case study can be important for understanding a part of the ecosystem services that food forests provide. The value of carbon is widely debated, depending on the variables (e.g., region, industry): there are carbon prices in the form of taxes on carbon and Emissions Trading System (ETS). Both value carbon, which is relevant for this study because the ecosystem service needs to be valued for improving the uptake by farmers, investors, policymakers and decision makers.

The mitigation impacts will change depending on carbon values, which is proposed between 0-150$ per ton of carbon (Toensmeier, 2016).

Agroforestry practises and scientific research have been carried out more extensively in tropical regions (Torralba et al., 2016). A minor part of agroforestry is based in Europe, in which only 0.7% of the Dutch agricultural land applies agroforestry (den Herder et al., 2017). Only small fraction if this share consist of food forest, about 120 hectares in the Netherlands, which is rapidly increasing (Green Deal voedselbossen, n.d.). The sequestration of agroforestry has been assessed in Europe, and has been found to vary between 0.09 to 7.29 $t\ C\ ha^{-1}\ yr^{-1}$ (Kay et al., 2019). Yet, the overwhelming majority of this study focuses on Mediterranean regions. Therefore, further research on other regions such as Northern Europe is needed (Mosquera-Losada et al., 2018). One of the recent initiatives, the Dutch National Monitoring Program Food Forests (NMPFF), started analysing food forests in the Netherlands to increase knowledge for several value, including the carbon uptake. However, this standardised plot-based method requires at least five years of research. In the meantime, there is a critical need for improved methods and reliable data concerning the impact of the carbon cycle, such as the mitigation potential in agroforestry (e.g. food forests) systems by carbon sequestration in biomass, soil or a reduction of emissions (Ravindranath & Ostwald, 2008).

This thesis aims to address the value of carbon in food forests, which can potentially play a role in (i) supporting farmers in the transition, (ii) financing carbon farming, and (iii) removing policy barriers. These strategies are stated in Toensmeier (2016) as necessary for increasing the uptake of carbon farming initiatives. However, as many fields are still unstudied, Kay et al. (2019) suggest that future research should improve the analysis of the potential of agroforestry, specifically carbon sinks, to look on a regional scale to improve data resolution. Furthermore, reducing the uncertainties in the monitoring and verification of agroforestry is an essential step in improving the uptake of agroforestry (COWI Institute Ecological & IEEEP, 2021). As a result, the following research approach is chosen.

This research analyses an in-depth case study of a food forest in Haarzuilens, a showcase forest, because of its chronosequence of 5.5 years. A chronosequence means that the different stages of the system are similar in approach but were planted in different years and can be compared to a reference situation. This layout may provide a better understanding of the carbon uptake and build-up while only analysing it within half a year. Furthermore, by understanding the differences over time in carbon sequestration and emissions, we may come closer to understand the environmental impact of food forests in temperate regions such as the Netherlands. This approach can be used to verify the current approach of NMPFF while already developing a better understanding of the transition of grassland to a food forest.

Industrial Ecology

The approach of food forests is closely related to Industrial Ecology, as it aims to improve industrial systems (in this case, agriculture), reducing (harmful) pollutants, by a system that is in harmony with the environment Furthermore, Industrial Ecology studies how industrial systems function in relationship with the biosphere to adjust the system to harmonise with natural ecosystems (Erkman, 1997). Therefore, understanding the ecosystem service of temperate food forests attempts to improve the uptake of more natural agricultural (eco)systems. In detail, this study analysis the carbon sequestration, one of the ecosystems of food forests (Torralba et al., 2016). Also, a carbon footprint based on the emissions measured in the field was obtained. This analysis is the possible foundation for future LCA, which is an important tool in Industrial Ecology (Kaufman, 2012). As LCA drastically increased the need for data (Kaufman, 2012), of which carbon footprints and quantification of the carbon stocks improves the LCA analysis of temperate food forests. The carbon footprint is the global warming potential (GWP) expressed in CO_2-equivalent, which is one of the categories in LCA (Weidema et al., 2008). In addition, the ecological perspective is linked to the social implication, which is fundamental in Industrial Ecology (Huppes & Ishikawa, 2011). This social implication addresses the value if farmers potentially value the carbon sequestration of switching to food forests and address how this relates to the Dutch climate targets.

Materials and methods

Quantitative methods were used to gain insight and verify the patterns of the carbon in the transition from grasslands to food forests. Various methods were used to determine the carbon stocks and emissions, which are divided into aboveground, belowground carbon, and carbon flux. A specific section describes the allometric equations within the aboveground carbon, as this is vital for estimating the carbon. Primary data was gathered, as these forests have no scientific basis yet. The most suitable method to monitor carbon pools was a specific field study because this approach provided actual location-specific data (Ravindranath & Ostwald, 2008).

Study System

The in-depth case study analysed a Dutch food forest located in Haarzuilens (52.123800" N, 5.005000" E), named "LekkerLandgoed", near a lake called "Haarrijnse Plas". The forest covers almost six hectares of land. The first planting started in the end of 2015 (Fig 1. A1-A2). The area is planted across a chronosequence, a time gradient, which implies that the different fields are planted over the years, giving it a unique layout for monitoring the carbon pools. The soil type consists mainly of clay (50-60%) (Van Dam, Bongiorno & Veen, 2021). The two oldest areas (Fig 1. A1-A2) were raised and are a romantic type of food forest: the trees are scattered, which gives the area a natural or park-like look. The younger types are rational types, which are more structured and beneficial for harvesting.

Grassland is the primary agricultural land-use type in the Netherlands (CLO, n.d.), which is also the former land use of the food forests. This is why the reference plot in this project is an organic grassland (Fig 1.E). The farmer applies around 170 kg N/ha of slurry, which functions as organic fertiliser (P. van Rossum, personal communication, April 25th 2021). This site is mowed to gain its nutrient-rich grass and fed to the cows.

Figure 1. Area mapped in order of years, A1-A2: 5.5 years old; B: 4.5 years old; C: 3.5 years old; D: 2.5 years old; E: reference plot of organic grassland.

Carbon stocks

The key carbon pools were identified in order to answer how the carbon stock develops over the chronosequence of 5.5 years. The IPCC (2003; 2006*)* stated how five carbon pools impact land management and forestry activities. These pools are:

1. Above Ground Biomass (AGB)
2. Below Ground Biomass (BGB)
3. Litter
4. Deadwood
5. Soil Organic Carbon (SOC)

The AGB, BGB and SOC are essential in carbon mitigation projects and related projects such as reforestation or agroforestry (Ravindranath & Ostwald, 2008). In addition, the litter layer will be included, as this was recommended in earlier research of young temperate food forests (Buinink, 2020).

Aboveground carbon

In a food forest, the AGB exist of different categories, namely grass, shrubs, fruit and nut-bearing trees, and coppices (Nair, 2016). This study applied the plotless and plot-based method described in Ravindranath N. & Ostwald (2008) to analyse the aboveground carbon pools. The sampling size for the tree species were the entire plots (Fig. 1). A plot-based was applied for the non-woody species (e.g., grass and herb, and litter), using a square-shaped plot (0.5 x 0.5m), as this is the most suitable for estimating the biomass (Ravindranath & Ostwald, 2008).

Parameters for the woody species are height, diameter at breast height (DBH), basal area, species and density (Ravindranath & Ostwald, 2008). The diameters of the nut and fruit-bearing trees were previously measured in 2020 by Dr M.J.J. Schrama (M. Schrama, personal communication, March 3th 2021). Altogether, almost 2500 trees over the chronosequence were identified and measured (in detail in Appendix A.3). The remaining pools included grass and herbs, litter, hedges, and coppices.

The above-ground sources of carbon are gathered similarly for litter, grass and herbs. Firstly, the litter was collected by the harvesting method (Ravindranath & Ostwald, 2008), at the beginning of March, before the growth period in the spring. Subsequently, the grass and herb production were collected in the following three months at the exact location as the litter. A bamboo frame of ¼ m^2 was used in which the ground layer was collected in paper bags, as these are useful when drying in the oven. The bags were dried in an oven of 40 degrees Celsius for five days to determine the dry weight of the litter layer (in detail in Appendix A.1). Five replicates in each category were used with the exact locations as NMPFF (Buinink, 2020) and earlier soil research (Van Dam et al., 2021).

Estimation of carbon in biomass

The following equations were retrieved from UNFCCC (2013), a method commonly used for estimating the aboveground carbon in trees. This approach was also applied in the NMPFF, which is important to note for verifying the accuracy of that program.

$$C_{tot=} \frac{1}{10^6} \cdot \frac{\sum C_{tree,}}{A} \quad (1)$$

$$C_{tree=} B_{tree} \cdot Cf \quad (2)$$

$$B_{tree=} V_{tree} \cdot DW \cdot BEF \quad (3)$$

$$V_{tree=} \pi \cdot r^2 \cdot h_{cm} \quad (4)$$

The total amount of the stored carbon (C_{tot}) is addressed in tonnes of carbon per ha^{-1} $(t\ C\ ha^{-1}\ yr^{-1})$ in each plot. This amount can be calculated by the sum of the carbon stored in trees in grams (g) divided by the area size (A) per hectare. The carbon per tree ($C_{tree)}$ was achieved based on the biomass of the tree and the carbon fraction (Cf), which is fixed at 0.47. The biomass tree (B_{Tree}) stored aboveground (g) was collected by the volume and wood density of the species (DW_g)(g cm^{-3}) and the biomass expansion factor (BEF), which is fixed at 1.15 (UNFCCC, 2013). The wood density was collected based on the species or family name (ICRAF, n.d.), if no density was found, the mean density was chosen of the species family. The volume of the tree (V_{tree}) was calculated (cm^3), by the radius (r^2) at breast height and the height in centimetres (h_{cm}).

In order to measure the volume, conventional biomass estimations use the diameter at breast height (DBH), which is 130 cm above ground. However, this excludes most young trees (<130 cm. On the contrary, this study did focus on young trees specifically, which required an adaptation of the conventional method. Therefore the trees were measured at diameter at knee height (DKH) (60 cm), as commonly used in other young forestry-related studies (Buinink, 2020; Jónsson & Snorrason, 2018; Otieno, Onim, Bryant, & Dzowela, 1991).

However, when using the stem biomass formula, the DKH needs to be converted to DBH, an essential condition for calculating the AGB. A subset of twenty-five trees within each category (e.g., coppice, fruits and nuts, and hedgerows), was measured with either DKH and DBH. Then, a statistical analysis was performed to verify the reliability of the correlation between DKH and DBH. As this condition is crucial for further assessing the AGB, the relationship needs to be very strong in each category, between 0.8 and 1.0 (Rea and Parker, 1992). As a result, the based area of at DBH can be calculated based on the power function of DKH:

$$BA_{DBH} = \alpha \cdot (BA_{DKH})^{\beta} \quad (5)$$

Another variable for estimating the volume is the height. Allometric equations can be used to estimate the biomass of the trees, of which the diameter is the most critical variable (Boosten & Snoep, 2021). Therefore, allometric equations were established to model the biomass purely based on the diameter. In order to generate an allometric equation, the height of the trees was measured for twenty-five trees using the instrument method (Ravindranath & Ostwald, 2008, p140). By combining the angle to the top of the tree (tan α) multiplied with the distance to the tree in meters (D_m), and in addition the height of the mobile (fixed at 1.5m) (h_{mob}) the height can be calculated:

$$h_{cm} = (tan\, \alpha \cdot D_m + h_{mob}) \cdot 100 \quad (6)$$

Whereby h_{cm} is the height of the tree in centimetres. A correlation between the height of the tree and the basal area was performed. The basal area is the cross-sectional view of the tree, which can be calculated by a power function of the basal area at breast height (BA) in cm:

$$h_{cm} = \alpha \cdot (BA_{DBH})^{\beta} \quad (7)$$

Then, the biomass in the subsets was measured to draw a calibration line between the tree biomass calculations based on the diameter. Three subsets of trees within each category (e.g., coppice, fruits and nuts, and hedgerows) were analysed to design a specific allometric equation and improve accuracy. The most commonly applied mathematical model in allometric equations for biomass equations is the power function (Muukkonen, Picea & Pinus, 2007). The variable is mostly DBH and will result in the volume or biomass. Therefore, the equation used for the coppice and hedgerow is:

$$C_{tree,g} = \alpha \cdot DBH^{\beta} \quad (8)$$

In contrast, the wood density changes due to the heterogeneity in species of the fruits and nuts; therefore, the volume equation is used. Afterwards, the wood density and biomass expansion factor are incorporated manually. The volume was calculated based on the power function of the DBH:

$$V_{DBH} = \alpha \cdot DBH^{\beta} \quad (9)$$

The various carbon pools were measured within each plot and scaled to the total stored carbon per hectare, as this is necessary for performing data analysis.

Belowground carbon

Two different pools were analysed to answer the amount of belowground carbon, namely the living belowground biomass and the soil organic carbon (SOC). First of all, the soil organic matter (SOM) was retrieved from a previous soil study (Van Dam et al., 2021) in which the wet digestion (Walkey and Black) method was applied. The SOM was measured at a depth of 20 cm in each plot (Van Dam et al., 2021). Consequently, the SOC was collected by a conversion factor of SOM and the bulk density. Previously, 0.58 times the SOM was used for calculating the SOC; however, recent research claims this should be 0.5 for a realistic estimation of the carbon content in the SOM (Pribyl, 2010). Additionally, the bulk density was measured according to the tube core method (Ravindranath & Ostwald, 2008). A soil core was sampled, dried at a constant 105 degrees Celsius for 24 hrs, and weighted.

For answering the amount of belowground biomass, a root-to-shoot ratio was applied, a commonly used method for such an estimation (Ravindranath & Ostwald, 2008). There is no scientific basis for allometric equations in temperate regions; therefore, the root-to-shoot ratio is used in this project. Previous research analysed the average ratio over 160 studies, of which the average is 0.26 times the aboveground biomasses (Cairns, Brown, Helmer, & Baumgardner, 1997). The value can differ between species, yet this ratio gives a reasonable estimation of the living belowground biomass (Ravindranath & Ostwald, 2008).

Data analysis of the above and belowground carbon

Firstly, for the aboveground carbon, the relationship between DKH and DBH was assessed based on the model fit of both independent variables. Accordingly, the allometric equations were modelled based on the DBH and carbon or volume. The projected curve was examined using the coefficient of determination (R^2), testing the strength of the relation among the independent and dependent variables. Additionally, the adjusted R^2 was used to take into account the predictors that are not significant. The closer the value is to 1.0 the better it can be used for future forecasting. All fruit and nut-bearing trees were measured in the area; therefore, some trees needed to be excluded if they were located outside the plot boundary. This was performed by QGIS (v.3.18), a geographical information system (GIS). By saving the measurement geographically, it is replicable for further research. Additionally, a database was built in excel (v.16.16) to calculate the carbon stocks.

The data analysis was performed by using R (version 4.1.0). In order to test the observed pattern, the mean of each year in the chronosequence was compared to the other years, which is performed separately for each category (e.g. SOC, grass and herb, litter, coppice, hedges, fruits and nuts). The case study was analysed by including and excluding site A1, as the soil characteristics were notably different (Van Dam et al., 2021). First, the homogeneity of variances was quantitively tested by a Levene's test, as tested to be robust (Lim & Loh, 1996). If equally distributed (p-value > 0.05), a Student's T-test was conducted, yet if the hypothesis was rejected, a Welch T-test was used. These T-tests showed whether the years are statistically different from the other sites of which significant difference was set at alpha of 0.05. The two independent variables in the test were age and carbon; carbon for the woody species was the mean carbon in the trees' biomass; for the non-woody species, the mean carbon per hectare was based on the five replicates. In order to find the regression which is most predictive for the carbon pattern observed from the first 5.5 years, a power function, a linear function, an exponential function, a logarithmic function and at last a polynomial function were used. The highest adjusted R^2 value was chosen among each carbon pool categories.

Carbon sequestration

The stock change over the years is between the sequestration potential of trees or the area. This is also based on the method described in UNFCCC (2013). The sequestration is the change of the various plots based on their year of plantation. The above and belowground biomass and the SOC sequestration rates were calculated separately to understand the differences between these pools, which can be calculated by $\Delta C_{\text{sequestration,biomass}} = \Delta C_{\text{AGB}} + \Delta C_{\text{BGB}}$ and $\Delta C_{\text{sequestration,total}} = \Delta C_{\text{SOC}}$.

GHG emissions

Besides, for answering the carbon flux patterns from grassland to food forests, the manual chamber method has been applied, a versatile approach for analysing the experimental effects at a plot scale (Lucas-Moffat et al., 2018). This method did analyse all three primary greenhouse gasses (GHG), namely, (i) carbon dioxide (CO_2), (ii) methane (NH_4), and (iii) nitrous oxide (N_2O). A collaboration with the department of terrestrial ecology at the Netherlands Institute of Ecology (NIOO-KNAW) was established. They supported the flux chamber method and formulated a protocol to measure soil greenhouse gas fluxes in the field. This protocol included 13 steps (Drost & Bodelier, 2017), which were applied accordingly, as stated in Appendix B. In the field, six samples were measured in each chamber, having three replicates in each site of the chronosequence. Due to limited chambers, site A1 was excluded from the analysis. Additionally, A2 was either included or excluded, because site raised and higher compared to the water table level, which can influence the carbon flux (van Huissteden et al., 2006)

The GHGs were measured in ppb (e.g. N_2O, CH_4) and ppm (e.g. CO_2). The amounts of moles were of each measurement was obtained based on the Ideal Gas Law (Collier, Ruark, Oates, Jokela, & Dell, 2014). This equation can be written as $n = \frac{PV}{RT}$ to obtain the moles of GHG per cubic metre. The temperature (T) was set at 296 Kelvin, which was based on the field measurement. The gas constant (R) is $8.205 \cdot 10^{-5}$, and the pressure (P) was assumed to be 1 atm. The flux (F) was calculated based on the slope (S) of the regression in moles per cubic metre, the volume of the chamber (V), and the chamber area (A), which can be written as $F = \frac{S \cdot V}{A}$. The volume of the chamber was fixed at 0.035 m^{-3} and the area of the chamber at 0.07065 m^{-2}. Lastly, the moles of each time series were converted to grams based on their molecular weight (ConvertUntis, 2021).

Data analysis of the carbon flux

First of all, the slope of the moles per GHG in the chambers was obtained by a linear regression. These slopes were based on the time series of six measurements in each chamber. The linear regressions of each chamber visually inspected, in order to analyse the goodness of the fit (Collier et al., 2014). Subsequently, the linear model of each time series was tested by ANOVA, to test whether the linearity is statistically significant. If the time series in one of the chambers were not significantly linear, this replicate was excluded in the further analysing of the flux.

In order to compare the measured GHGs fluxes, they were represented in terms of carbon footprint. This entails that all three gasses were scaled to their global warming potential (GWP) for a 100-year time horizon relative to CO_2. The IPCC showed the GWP values, of which the values with climate-feedback loops were chosen, namely: 1 for $\mathrm{CO_2}$, 34 for $\mathrm{CH_4}$, and 298 for $\mathrm{N_2O}$ (IPCC, 2013). The climate-feedback values values might have higher uncertainties, yet these numbers are greater and give a more complete and conservative analysis (Trottier et al., 2015). The calculated CO2-equivalents was modelled based on age and flux. A linear regression analysis showed the goodness of the fit of each GHG over the time series measured. Additionally, the carbon footprint of the three GHGs together was analysed to show if an overall decreasing or increasing trend occurred in the chronosequence.

Valuing the carbon sequestration

Carbon credits are generally valued in $\mathrm{CO_2}$, while this case study measured the carbon stocks. Therefore, the carbon was multiplied by $\frac{44}{12}$, as this is the ratio of molecular weight of carbon dioxide ($\mathrm{CO_2}$) and the atomic weight of carbon (C) (Boosten & Snoep, 2021). Based on this calculation, the amount of credited carbon can be determined. The carbon sequestration included and excluded the SOC, as this differs along other carbon offsets (Manley, Kooten, & Moeltner, 2003). In this case, the variation between the SOC measurements differed notably; therefore, the average sequestration of the first 5.5 years was used. The sequestration rates in above and belowground biomass were analysed for each site specifically, as this is the crucial carbon accounting pool (Boosten & Snoep, 2021). As the carbon flux was a one-time measurement, this was not included in the carbon accounting.

Many price predictions exist, yet some of them are already outdated, due to the radical price increase in 2021 (Meredith, 2021). This study uses multiple prices, due to the uncertainties in price predictions, the prices were stated in OECD (2021) as three carbon benchmarks; 30 €/$\mathrm{tCO_2}$ (low), 60 €/$\mathrm{tCO_2}$ (med), 120 €/$\mathrm{tCO_2}$ (high). These prices are the benchmarks of the average carbon price till 2050, which value the food forests based on the sequestration rates. The average price during June to July in 2021 was 53 €/$\mathrm{tCO_2}$ (Sandbag Climate Campaign CIC, n.d.), thus currently it is closest to the middle benchmark of 60 €/$\mathrm{tCO_2}$.

Results

Carbon stocks

Quantification of aboveground stocks based on allometric equations

To be able to come with an overarching formula for estimating all woody carbon pools, a set of allometric equations were formulated for each category (e.g. coppices, hedgerows and fruit- and nut-bearing trees) (Table 1). First, the relationship between the basal area at knee height (BA_{DKH}) was tested compared to basal area at breast height (BA_{DBH}), which showed a R^2 and an adjusted R-value of above 0.8 in all three categories, which is very strong (Rea and Parker, 1992). Furthermore, the observed relationships between the basal area at breast height and the tree's height for coppice, hedgerows, and fruit- and nut-bearing trees were 0.85, 0.76, 0.84 (adjusted R values) respectively. Nevertheless, an even stronger relation was observed between basal area at breast height compared to either the volume or the carbon per tree (Table 1). Therefore, the relationship between BA_{DKH} and BA_{DBH} was verified, and the remainder of the report is purely based on DKH and the carbon or volume equation.

Table 1. The allometric equations formulated for estimating the carbon stock for each type in the woody carbon pools. The equations are all power functions, α and β are the parameters of which α is the scaling factor and β the elasticity. The R^2 is the coefficient of determination is the repeatability measure of the equation that determines whether variances in the dependent variables was explained by the independent variables. The adjusted R^2 takes into the account the degrees of freedom of the equation.

Category	**Equation**	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	$\boldsymbol{R^2}$	**Adjusted** $\boldsymbol{R^2}$
Coppice	$BA_{DBH} = \alpha \cdot (BA_{DKH})^{\beta}$	0.5961	1.0654	0.973	0.970
	$\mathrm{C}_{\mathrm{tree}} = \alpha \cdot (BA_{DBH})^{\beta}$	38.145	1.3249	0.989	0.986
Hedgerow	$BA_{DBH} = \alpha \cdot (BA_{DKH})^{\beta}$	0.4711	1.2165	0.927	0.917
	$\mathrm{C}_{\mathrm{tree}} = \alpha \cdot (BA_{DBH})^{\beta}$	56.326	1.2865	0.986	0.980
Fruits/nuts	$BA_{DBH} = \alpha \cdot (BA_{DKH})^{\beta}$	0.4472	1.1843	0.941	0.933
	$V_{DBH} = \alpha \cdot (BA_{DBH})^{\beta}$	185.2	1.1860	0.995	0.993

Estimations of aboveground carbon

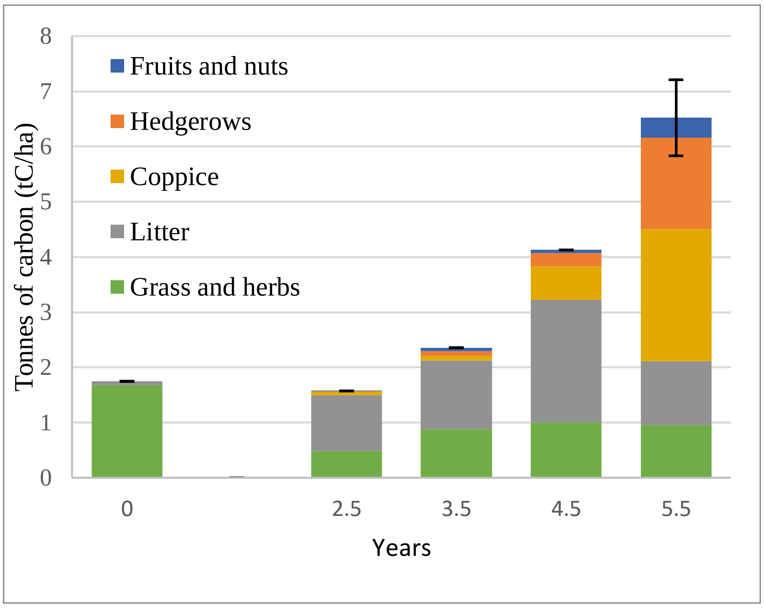

Figure 2. The total rate of build-up in the aboveground carbon pools of the chronosequence from grassland (year 0) to food forest.

The results of the carbon estimation based on the allometric equations and harvesting method showed that the food forests LekkerLandgoed stored 1.7 $t\,C\,ha^{-1}$ in the aboveground biomass in the grassland (year 0) and a mean of 6.5 $t\,C\,ha^{-1}$ in year 5.5 of the food forest. The two replicates in year 5.5 differ between 5.8 (A1) and 7.2 (A2) $t\,C\,ha^{-1}$. A general increase in aboveground carbon occurs (Figure 2), but the patterns between the various components exhibit a number of pronounced differences (see Figure 5 and Appendix C), below these differences will be elaborated.

The herbaceous layer (e.g. grass and herbs) were the highest contributor in the grassland yet decreased significantly after switching to a food forest (Fig. 3A). Nonetheless, between years 2.5 and 3.5, an increase was observed, yet after year 3.5, no notable variation occurred in the carbon content of the herbaceous layer. Besides, the share of carbon in the litter layer increased consistently in the first 4.5 years (Fig. 3B), of which year 4.5 was the highest, 54% of the total aboveground carbon. Thus, in total, the ground layer (e.g. grass and herbs, and litter) was the main contributor to the carbon in the first years, namely 90% of the aboveground carbon in the 3.5-year plot, yet this share decreased over time, 78% in year 4.5, and 32% in year 5.5 (Fig 2). Hence, even though the herbaceous layer did not decrease in the last years, the litter layer did between 4.5 and 5.5, but more importantly, the share of woody species grew fast.

The woody species (e.g. coppice, hedges, fruits and nuts) together have exponential growth ($R^2 = 0.999$) over the first 5.5 years (Fig. 3). First of all, the coppice on its own grew exponentially ($R^2 = 0.96$). A notable growth was observed between the years 4.5 and 5.5, with a mean growth per tree of roughly 360%. In addition, the oldest plots had two replicates that differed, site A1 had 2.1 $t\ C\ ha^{-1}$, while site A2 had 2.7 $t\ C\ ha^{-1}$ of carbon in the coppice pool. The coppice was the main contributor to the total aboveground carbon in year 5.5, namely 37%.

Additionally, the hedgerow also showed an exponential growth ($R^2 = 0.94$). The share of the hedgerows was 25% in year 5.5, of which site A1 stored 1.6 $t\ C\ ha^{-1}$, while site A2 stored 1.7 $t\ C\ ha^{-1}$. (Fig. 3D). Finally, the carbon content of the fruit- and nut-bearing trees grew slower than the other woody species (Fig. 3). Nevertheless, the regression analysis showed an exponential growth ($R^2 = 0.85$). A significant increase emerged between the years 4.5 and 5.5, showing a mean growth per tree of roughly 600%. Also, negligible variation was observed between the two 5.5-year-old sites (Fig. 3D). Still, the share of fruit and nut trees related to the total aboveground carbon was only 1.3% in year 4.5 and 5.6% in year 5.5.

Estimations of soil organic carbon

The total soil organic carbon (SOC) in this case study did not exhibit a specific trend in the first 5.5 years (Fig. 4). The regression analysis of the SOC showed statistically negligible change over time ($R^2 < 0.1$). The graph depicted in Figure 4 illustrates the development in this transition over these years. The average SOC was 112

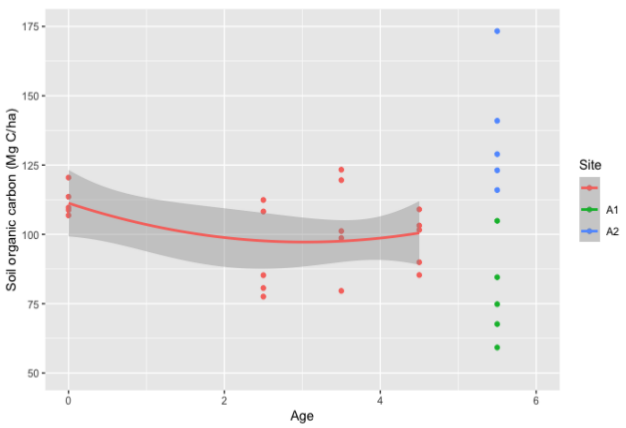

Figure 4. The soil organic carbon (SOC) measurement scattered over the various years.

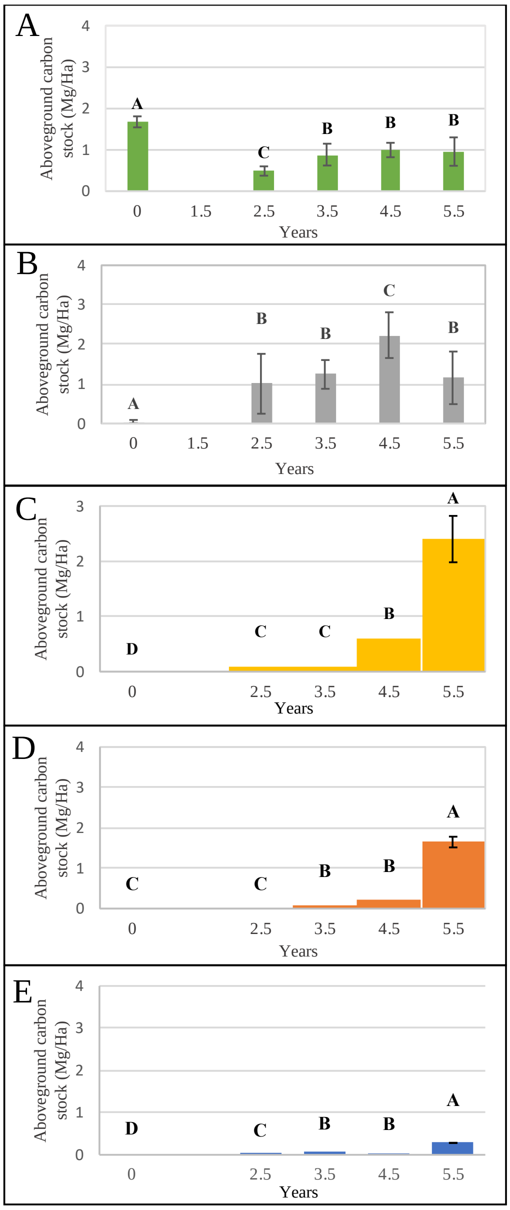

Figure 3. The total aboveground carbon in each compartment: A: grass and herb; B: litter; C: coppice; D: hedgerows E: fruits and nuts.

The error bars indicate the standard deviation between the various replicates.

The letters A, B, C, and D indicate a significant difference at alpha of 0.05. A is the highest value that is significantly different from year stated as B, while B is significantly different from years A and C.

$t\ C\ ha^{-1}$ in the grassland (year 0) and 107 $t\ C\ ha^{-1}$ in the oldest food forest plot (A2). Therefore approximately

-7 $t\ C\ ha^{-1}$ might be released from the SOC over the first 5.5 years. A decrease occurred after changing the land's function of the grassland, yet not statistically significant (Fig. 4). After year 2.**5**, no clear pattern was observed. As can be seen, the means of the older plots are notably different, namely 78 $t\ C\ ha^{-1}$ (A1) and 136 $t\ C\ ha^{-1}$ (A2). By excluding site A1 a negligible regression remains linearly ($R^2 < 0.1$), yet in polynomial regression, this is relatively strong ($R^2 = 0.4$).

Determination of carbon sequestration

The carbon sequestration results were divided into the above and belowground biomass (Fig. 5) and SOC (Fig. 6). First of all, the ABG and BGB biomass had exponential growth (Fig. 5). Figure 7 was categorised by the biomass with the ground layer (Fig. 5: blue) and the living biomass in woody species (Fig. 5: orange). As seen in the first year, minor negative sequestration occurred, yet from year 2.5 onwards, notable exponential growth was observed. The mean sequestration between years 4.5 and 5.5 was 3.0 $t\ C\ ha^{-1}\ yr^{-1}$ in the biomass with the ground layer (e.g. grass, herbs, and litter). Hence, the oldest plot had two replicates, varying between 2.2 (A1) to 3.9 (A2) $t\ C\ ha^{-1}\ yr^{-1}$. For the biomass of the woody species, a mean sequestration of 4.4 $t\ C\ ha^{-1}\ yr^{-1}$ appeared in year 5.5 (Fig. 7: orange). Consequently, this sequestration rate was based on 3.9 (A1) and 4.9 (A2) $t\ C\ ha^{-1}\ yr^{-1}$.

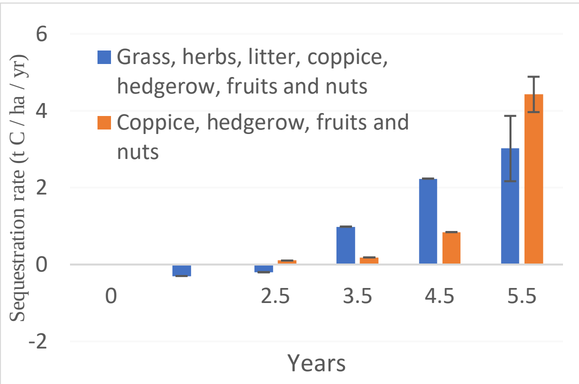

Figure 5. The total sequestration in above and below ground carbon of the living biomass and litter.

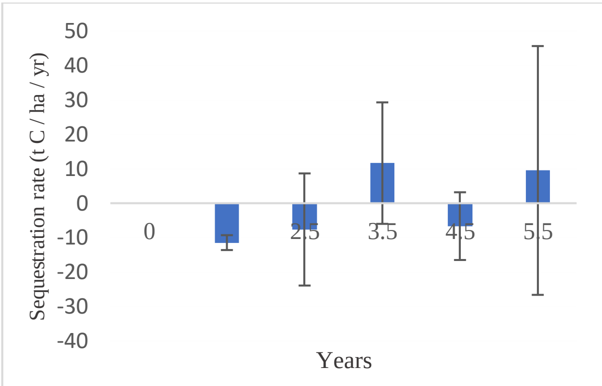

Figure 6. The total sequestration in soil organic carbon (SOC) in each plot.

In contrast, the development of the SOC did not present a clear pattern (Fig. 6). The SOC had negative sequestration initially, indicating a release of carbon of approximately -7.6 $t\ C\ ha^{-1}\ yr^{-1}$. However, after year 2.5, positive sequestration of 11.7 $t\ C\ ha^{-1}\ yr^{-1}$ was observed, yet this increase was not significant due to the variation between the measurements. Consequently, negative and positive sequestration was observed, -6.6 $t\ C\ ha^{-1}\ yr^{-1}$ and 9.5 $t\ C\ ha^{-1}\ yr^{-1}$ in years 4.5 and 5.5 respectively. The sequestration over the first 5.5 years was on average -0.8 $t\ C\ ha^{-1}\ yr^{-1}$. The error bars show the standard deviation of the measurements, a positive sequestration appeared when site A1 is excluded, while a negative if site A2 is excluded.

Carbon emissions

The observed trend in the carbon emissions

The chamber carbon flux measurement results (Fig. 7) showed three different trends within the GHGs (CO_2, CH_4, N_2O). Overall, a moderate model fit was observed in a negative trend in CO_2, while a negligible trend was found for CH_4, and a weak positive trend for N_2O. If year 5.5 was excluded, as this site has a higher elevation above sea level, a moderate negative regression appeared. CO_2 had the biggest carbon footprint in all sites; it was only surpassed in year 5.5 by N_2O. Comparing the means in the following years, only in the first 2.5 years a significant decrease was measured for CO_2. Over all the years, no significant difference was found for CH_4. Finally, N_2O only showed a very strong variation between years 4.5 and 5.5, yet all others were not statically significant.

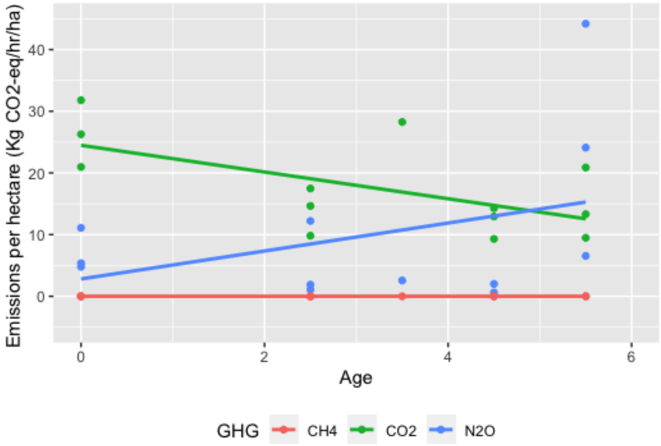

Figure 7. The carbon flux addressed according to its carbon footprint for each measured greenhouse gas (GHG).

The three emissions were combined based on the GWP, presenting all values in the CO_2-equivalent. However, no specific trend occurred in the carbon footprint based on the measurements of the first 5.5 years (Fig 8). This might address no difference in the carbon flux when switching to a food forest. However, if year 5.5 was excluded, as this site is raised, a strong negative regression appeared (Fig. 9).

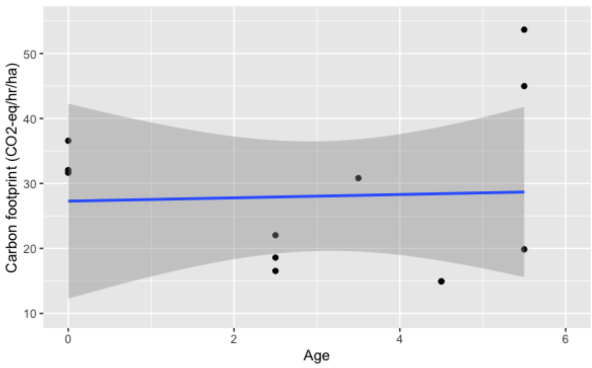

Figure 8. The carbon footprint and the corresponding trendline over all measured years.

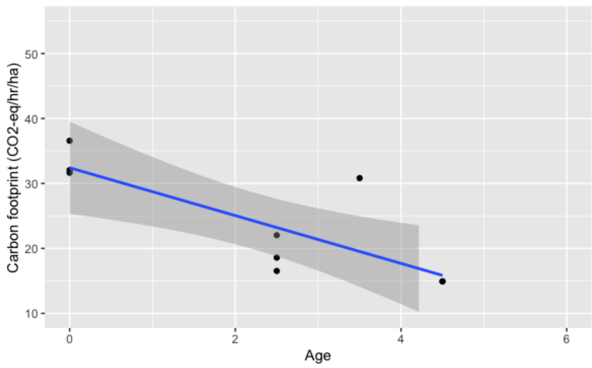

Figure 9. The carbon footprint and the corresponding trendline if year 5.5 is excluded.

Valuation of carbon sequestration

The value of carbon farming depends on two variables, the sequestration in above and belowground biomass and the price of carbon. However, due to the uncertainty, three carbon benchmarks were used, 30 €/tCO_2 (low), €/tCO_2 (med), 120 €/tCO_2 (high). The sequestration rates of years 3.5, 4.5, and both replicates of year 5.5 were presented when valuing the carbon sequestration (Table. 2). As can be depicted from the table, the value increases exponentially. Based on the latest sequestration rates in the biomass layer, the farmer can expect a compensation of 433 to 2,159 $€\ ha^{-1}\ yr^{-1}$. Although the SOC had a notable variation between the measurements, if the SOC was included, this would emit on average -0.8 $t\ C\ ha^{-1}$ (2.9 $t\ CO_2\ ha^{-1}$). Therefore, this illustrates the impact if SOC decreases over time.

Table 2: Projections of the value of carbon farming, based on biomass carbon stock and carbon price projections. The sequestration is scaled to the CO_2-equivalent for assessing the monetary value.

Site	**Years**	**Sequestration rate per year**	**30 €/tCO_2 (low)**	**60 €/tCO_2 (med)**	**120 €/tCO_2 (high)**
C	3.5	0.2 $t\ C\ ha^{-1}$ = 0.7 $t\ CO_2\ ha^{-1}$	€ 20.37	€ 40.75	€ 81.50
B	4.5	0.8 $t\ C\ ha^{-1}$ = 3.1 $t\ CO_2\ ha^{-1}$	€ 92.82	€ 185.64	€ 371.28
A1	5.5	3.9 $t\ C\ ha^{-1}$ = 14.5 $t\ CO_2\ ha^{-1}$	€ 433.89	€ 867.79	€ 1,735.57
A2	5.5	4.9 $t\ C\ ha^{-1}$ = 18.0 $t\ CO_2\ ha^{-1}$	€ 539.69	€ 1,079.38	€ 2,158.77

Discussion

Using a chronosequence of food forest planting stages, the results of this study show that the food forest can generate a significant increase in aboveground carbon, while the patterns for belowground carbon are markedly different. The exponential growth of aboveground carbon was mainly observed in woody species (e.g. coppices, hedges, and fruit and nut-bearing trees), closely resembling the start of an expected sigmoid curve of the growth of a forest (Birch, 1999). The litter dynamics seem closely related to the shift away from grass production, yet this stops in year 5.5. Often neglected in carbon estimations, the ground layer (e.g. herbaceous and litter layer) was the most apparent carbon source until year 4.5. The share of woody species is small initially but increases exponentially, becoming the most evident contributor in the latest stage, with coppice at 37%, hedgerows at 25%, while fruits and nuts remain low in their carbon contribution (6%). The belowground results suggest lots of variation after shifting to food forests, yet no specific pattern occurred. Overall, these results paint a mixed picture for the aboveground and belowground carbon pools, further discussed below.

Limitations of the present study

All results within this study are calculated based on the measurements converted by methods and allometric equations that have some inaccuracy. In the following paragraphs, I discuss the various factors which led to uncertainties within the chronosequence and the impact of these uncertainties, measurements during this case study and the corresponding calculations.

The chronosequence within this study might be influenced by variation in biotic and abiotic variables. A Biotic difference, for example, is the variation between sites; the trees' density and layout slightly differ. More replicates were needed to verify this difference, yet only the 5.5-year-old sites had two replicates, yet painted a mixed picture essentially in belowground carbon. A plausible explanation for this variation might be abiotic differences such as pH and moisture levels and higher amounts of sand in site A1 (Van Dam et al., 2021). Also, the former land use may not be completely identical, as the farmer previously owned some plots, while the other sites were part of *Natuurmonumenten*. Therefore, the null point may differ slightly, as management differs between those organisations. In addition, this study assumes that the grassland will be similar over the years, while a change in land management might impact the SOC. Nevertheless, the farmer assumed he would not change the grassland management in the following decades (P. van Rossum, personal communication, July 9th 2021).

The carbon stocks not only change based on time but also other factors such as drought, rain, pH, moisture, and other soil characteristics. Other variables such as droughts and rainfall are almost identical because of their proximity, yet this arises not exactly in the same year due to the age difference. Therefore, a drought in a site of one year has more impact than a five-year-old plot. As in 2018, 2019, and 2020 notable droughts occurred (KNMI, n.d.), the oldest plots were already several years old. This issue might impact the observed patterns, as the three following droughts can reduce the growth (Petrone et al., 2014). This might suggest an underestimation of the total carbon stock, yet the youngest are more sensitive to droughts. Also, droughts will be more common in the Netherlands (IGRAC, n.d.); thus also arise in newly established food forests. In addition, different soil types or former land use are notably affecting the carbon pools (Buinink, 2020), yet only the soil in site A1 is notably different.

As the carbon stocks and emissions are purely based on measurement, some uncertainties during the field work might influence the results. Firstly, the grass and litter were collected by a harvesting technique. There might be an inevitable overlap between the various harvesting moments. In addition, if the grass is harvested, the roots may die because of the root-to-shoot ratio. Thus, the grass seems to grow slower compared to the surrounding area. This indicates an underestimation of the herbaceous layer and this occurs in all plots. Additionally, the shrub layer was not entirely included within this analysis, which tends to grow fast in a young food forest. The shrubs may contribute to 8% of the total carbon content (Lehmann, Lysák, Schafer, & Henriksen, 2019); therefore, this exclusion suggest a slight underestimation of the entire carbon stock. Also, the fruits and nuts species were obtained from measurements in 2020, a time gap of around ten months with the other measurements. For example, a single *Prunus avium* tree showed an increase of nearly 30% in diameter in this short period, suggesting an underestimation of the fruits and nuts compartment. The conservative perspective in underestimations are better than overestimations in carbon accounting in forestry (Neeff, 2021). Lastly, the carbon flux was only feasible measuring once; this increased the uncertainty, as the annual average differs from the various seasons. Therefore, this measurement does not represent the change in seasons and years, yet the single measurement gave insights into the relative difference between the fields in a chronosequence, which can be compared based on the global warming potential (Pandey et al., 2011).

Finally, the trees are measured according to allometric equations, which is generally highly specific in location and species. These equations usually are a simplification, as harvesting was not suitable in this case. Three allometric equations were formulated specifically for this case study, of which only two of them are species specific (e.g. coppice, hedgerows). Therefore, the immense heterogeneity of the species in the fruits and nuts is not totally encountered. Nevertheless, the analysis showed a strong correlation within each subset. Still, it is feasible that the generalizability of the equation is not representing the other species. For example, sampling and laboratory errors might be present within the data collection (Ravindranath & Ostwald, 2008). Also, shrubs may require different equations than trees; therefore, using one of these equations impact the results. For example, in the study of NMPFF, most equations used in LekkerLandgoed are shrub equations (Buinink, 2020), while my research uses tree allometric equations. Whether to determine if it is a tree or shrub can be argued based on the shape or the species, this study classified the species (e.g. *Crataegus, Salix, Prunus spinosa*) as a tree because it mostly was one-stemmed at the measured height. This classification does impact the estimations of the carbon content yet is a common issue in estimations of carbon stocks in young forest (Buinink, 2020), as these might branch off below breast height.

Despite these limitations, the results quantitively assessed the carbon patterns in young food forests in temperate regions. In the paragraphs below, I address these points and draw a number of implications based on the results. First of all, the suitability of the method is addressed, and the overall key patterns will be discussed in-depth. Subsequently, the results were compared with comparable studies, especially with NMPFF, as this also measured LekkerLandgoed. In addition, the implication of the carbon footprint was addressed, and how this can complement the sequestration. Besides, the social implications were described in detail by valuing the ecosystem service for the farmers' and Dutch climate targets perspective.

Suitability of the method

The thesis used widely known methods in order to estimate the carbon stock. The biomass was estimated using the allometric equations, as this is the most suitable method for small scale case studies (Ravindranath & Ostwald, 2008). Even though this food forest has immense heterogeneity, it was categorised based on three different types (e.g. coppice, hedgerows, and fruits and nut-bearing trees). All allometric equations fitted very strongly with the measured trees. The plotless method was most suitable for measuring the trees, as this method has previously been acknowledged to be highly functional for single period estimation with limited personnel (Ravindranath & Ostwald, 2008). It was time-consuming yet the most appropriate way for small in-depth case studies. In addition, this approach had a high sampling size, as the whole area within the chronosequence was measured. This increased the accuracy of the estimation. Besides, for the non-woody species, the harvesting plot method is widely used and accurately assesses the carbon (Ravindranath & Ostwald, 2008). Altogether this provided a reasonable estimation of the aboveground carbon. Moreover, the tube core method is the most suitable method for determining the bulk density; however, generally, a low spatial variability occurs in these measurements (Ravindranath & Ostwald, 2008).

Because measuring all diameters at breast height (DBH) was not feasible, this study carried out the measurements at knee height (DKH). This study demonstrates a very strong correlation between DBH and DKH (Table. 1). This relationship is not familiar in previous studies, especially not for the hedges, which makes finding this strong relationship even more worthwhile. This finding contrasts with traditional biomass estimations of forests, yet either tree or shrub species in food forests might branch below breast height, which suggests the method of measuring DKH might be useful in future carbon estimations of food forests. Therefore, further research is needed to test the reliability of using DKH.

Patterns in aboveground and belowground dynamics of carbon farming

The results provide a quantitive insight into the carbon patterns in young food forests in temperate regions. The woody species carbon pool grew exponentially and will be the most important source for carbon estimation in the long term, especially the category. This type of woody species primarily exists of Willow (*Salix* spp.) and Poplar (*Populus* spp.), which are already acknowledged for their carbon sequestration potential of 3.5 and $4\ t\ C\ ha^{-1}\ yr^{-1}$ for willow and poplar respectively (Rytter, 2012). More coppice (canopy layer) trees are suggested to increase the carbon sequestration, yet considering the required sun availability for the food forests. In order to have more diversity and effective understorey, more light needs to surpass compared to a traditional forest (Limareva, 2014). Therefore, more research is needed to optimize the design to flourish by the available sunlight in the forests while reaching maximum carbon sequestration in the canopy layer.

Hedgerows also provide a notable contribution to the carbon stocks, as it contains 25% of the total aboveground carbon in year 5.5. A reason for this might be the density of three trees per meter, plus the fact that 80% of the total number of trees in these sites are in the hedgerows. The plots of age 5.5 had hedgerows on all sites, which increased the number of trees with roughly four times compared to age 4.5. This carbon source is not common in natural forests, nor is it acknowledged as a notable source for carbon sequestration (Schafer et al., 2019), yet occur in almost any temperate food forest (Lehmann et al., 2019). Hedgerows are estimated to sequester between 1 to 8 $t\ C\ ha^{-1}\ yr^{-1}$ while also can play a role in pest control and windbreaks (Toensmeier, 2016). This seems in line with the 1.64 $t\ C\ ha^{-1}\ yr^{-1}$ measured between years 4.5 and 5.5. Nevertheless, this still reflects a young hedgerow, thus can potentially increase. In this case, the hedgerows consist primarily of *Crataegus* species; these can reach heights of ten metres (Directplant, n.d.; Seasonal Gardening, n.d.), while the average height was three metres in the 5.5-year-old sites. Further research on food forests should include hedgerows on all possible edges in their carbon assessment and analyse their share in older food forests.

The grass production reduced notably after taking out intensive management and fertiliser use. Manure and machinery were only applied in the reference site (grassland), which provides evidence that the aboveground carbon changes after altering the land function. Also, a shift appears in the herbaceous layer of the older plots, as more edible species tend to grow instead of grass. The younger sites do not contain herbs within the herbaceous layer, while the older sites do contain edible herbs, of which nettles are the most dominant species (see appendix C). While the carbon assessment showed no notable change in the last two years of the food forests, still it changed the proportion of herbs and grass. Therefore, more research might be needed to further analyse the changes in the different components of the herbaceous layer.

The patterns in the belowground layer (e.g. SOC and belowground biomass) is markedly different compared to the aboveground. The SOC changes over the various years, especially after altering the land function. This suggests that the data is highly location-specific, as a disturbance of the soil affects the belowground carbon. The SOC in the soils might lose, gain or undergo negligible change during reforestation projects (Rytter, Rytter, & Högbom, 2015). Even though the patterns of above and belowground are notably different, the decrease at the beginning is in line with the findings of Ravindranath & Ostwald (2008), as oxidation occurs after management of the top layer. In contrast, Deng Zhu, Tang & Shangguan (2016) found no significant difference in the conversion from grassland to a forest at the short term, yet they found a significant increase in the long-term (> 10 years). Another contrasting research observed the transition over 100 years from grassland to forest, which led to a decrease in SOC (-7% ±27), but no significant trend was presented in this study (Poeplau et al., 2011). Altogether the various studies show a contrasting insight of the quantification in transitions towards forests. These results might suggest that the SOC content in year 5.5 is not valid, as it seems not possible to have this increase in such a short period (Poeplau et al., 2011). Both sites differ due to the raised soil, which might contain partly sand and peat (Van Dam et al., 2021). Therefore, a more plausible explanation is that organic carbon was already present in the raised soil, extracted from the top layer elsewhere, which also explains the low SOC content in the other 5.5-year-old plot.

A SOM between 10-20% is remarkably high, yet this might be in line with the 12-20% mentioned in Brady & Weil (1999). Also, Reijneveld, van Wensem & Oenema (2009) analysed grassland with clay soils (35±12% clay) in the Netherlands, resulting in a mean SOC of 5.6%. This study showed SOC values ranging between 5.81-6.86% for the grassland. The case study LekkerLandgoed is located at old river clay soils, which generally have higher SOC content (Lesschen, Heesmans, Mol-dijkstra, Doorn, & Verkaik, 2012). Although grassland has higher SOC levels than forests, purely based on soil type, forests generally have higher SOC content than grassland (Lesschen et al., 2012). They also mentioned that transitions from grassland to forest on old river clay soils positively impacted the SOC content in 15 years. However, this is not tested in 5.5 years. Therefore, further research needs to address whether this will change in the coming ten years, considering a sampling depth of 30 cm.

A reason for the large variation within the SOC measurements might be the characteristics of the topsoil layer. Previous studies found a very strong relationship between the bulk density and SOM (Ruehlmann & Körschens, 2009; Sakin, Deliboran, & Tutar, 2011). These studies state that SOM is affected by the soil structure, as well as pH influences the bulk density. This addresses how the large variation within the sites influences the uncertainty of addressing trends in the SOC estimations. A recommendation to reduce this uncertainty is adjusting the sampling depth based on the bulk density (Hairiah et al., 2020). They also suggest that compaction influences the SOC content, which explains the large variation in SOC compared to the grassland. Further research is needed to adapt the soil depth sampling based on the soil texture, decreasing the uncertainty of the SOC analysis. This might be crucial for determining the net carbon impact of the transition towards food forests.

Comparing results to those of the National Monitoring Program of Food Forests

A comparison with NMPFF is essential, as this organisation also studied LekkerLandgoed in 2020 by a plot method. This gives a reasonable verification of their more time- and cost-efficient method. The specific results for the food forests in LekkerLandgoed were markedly lower than in this research (Fig. 10: blue). The NMPFF focussed on woody species, this research showed how the ground layer is a crucial carbon pool for young food forests. If the ground layer is excluded, a more similar trend occurs (Fig. 10: yellow).

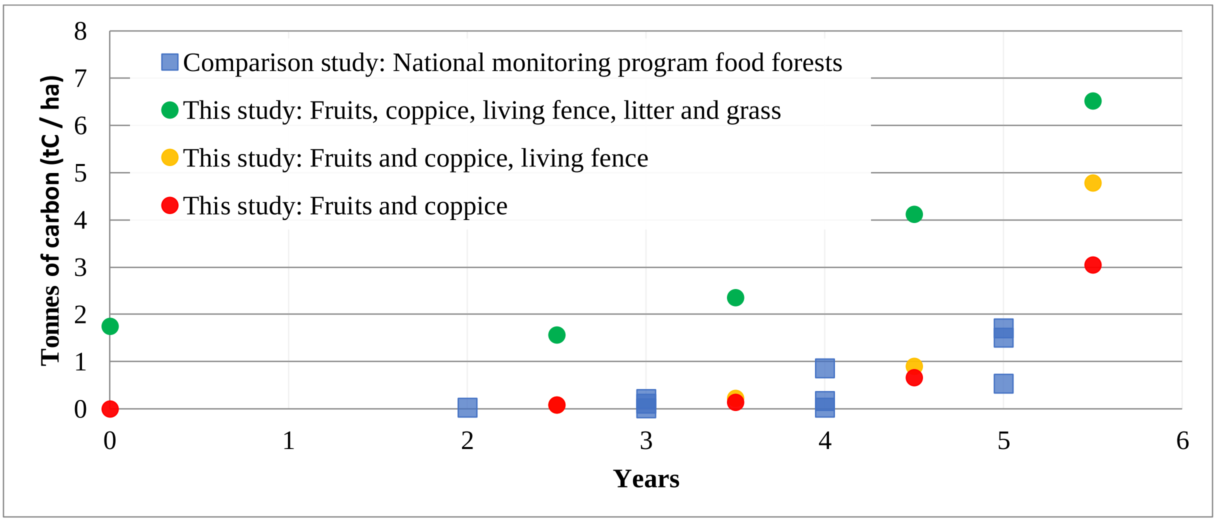

Figure 10. The total aboveground carbon of the years, comparing the results with the National Monitoring Program of Food Forests

Additionally, the hedges are an evident carbon pool, while these are primarily out of scope in the NMPFF, because their method removes all edges in the grid that are not entirely 100 square meters (B. Rooduijn, personal communication, June 12th 2021). If the hedges and ground layer are both excluded, the results seem in line with results of NMPFF (Fig. 10: red). Therefore, is suggested that the hedgerows on the edge of the plots need to be estimated separately by a plotless method. Also, if carbon stocks are used for carbon credits, the grassland baseline includes the herbaceous layer (Boosten & Snoep, 2021). Thus, this layer needs to be included if the carbon sequestration is used for carbon credits.

Impact of food forests on GHG emissions

The one-time carbon flux showed the trend of the three main GHGs emissions. The total carbon footprint of the GHG combined had no significant change, yet if year 5.5 was excluded, a strong negative regression appeared. The forest included both *Salix* and *Poplar*, which are nitrogen fixating plants (von Wuehlisch, 2011). Taking up nitrogen from the atmosphere can increase the CO_2 uptake, which reduces

CO_2 soil emissions (Templer, Pinder, & Goodale, 2012). This is in line with the negative regression found in the results. On the contrary, the positive regression in N_2O might not be explained by the nitrogen fixating plants (Templer et al., 2012), as a N_2O reduction is expected in Baah-Acheamfour et al. (2016), which found a reduction in agroforestry systems compared to conventional agriculture. If the year 5.5 was excluded, the N_2O flux is more in line with the literature, thus raised soils might influence the observations. Also, the CH_4 showed no significant change, while previous studies showed that planting trees will reduce all three main GHGs emissions (Templer et al., 2012). Overall, GHG accounting is a good addition for a comprehensive carbon estimation (Collier et al., 2014), including both CH_4 and N_2O for a better understanding of the carbon footprint (Baah-Acheamfour et al., 2016). However, the one-time measurement within this case study did not complete the annual flux and not verified some measurements. Therefore, an annual flux is required in order to value the carbon footprint monetarily.

The potential value of carbon sequestration in food forests LekkerLandgoed

The method of valuing ecosystem services is significantly affecting the outcomes (Hein et al., 2020). An important driver for carbon farming is a stable carbon price, as this supports initiatives to sequester carbon. There are many projections concerning the carbon price varying between €10 to €350 (The World Bank, 2021). Even during this six-month project, the ETS carbon price has risen by approximately €25. This growth over the last period is faster, as projected earlier (Brink, Vollebergh & van der Werf, 2016). Both the price and carbon uptake are uncertain for the near future. Currently (July 2021), the carbon price is slightly above €50 (Sandbag Climate Campaign CIC, n.d.), and this price is projected to reach €180 by 2050 (Grosjean et al., 2018).

Additionally, the carbon content is crucial for valuing the food forests. Previous research has shown that the growth of forests generally follows a sigmoid curve (Birch, 1999; Buinink, 2020). Thus, at some point, the curve should plateaux out, yet at this stage, uncertain when this would happen. Two mature (> 20 years) food forests with former grasslands showed a carbon content in biomass of 19 to almost 70 $t\ C\ ha^{-1}$ (Buinink, 2020), and 39.53 ± 4.05 $t\ C\ ha^{-1}$ (Schafer et al., 2019). this study's results do not precisely fit this projected sigmoid curve, as already at the age of thirteen, the 40 $t\ C\ ha^{-1}$ might be reached. In comparison, the average sequestration in forests in the Netherlands is 1.5 $t\ C\ ha^{-1}\ yr^{-1}$ (Schenau et al., 2021). This could point out an overestimation in this study, but a more plausible explanation will be that this food forest has higher carbon sequestration potential. Because a factor that increases production is higher SOC amounts (Milne & Ehqhàwv, n.d.), and this site has higher SOC compared to other clay and sandy soils (Lesschen et al., 2012).

The results showed a compensation of 434 to 2,158 € $ha^{-1}\ yr^{-1}$ based on the sequestration rates between years 4.5 and 5.5. As the prices are still uncertain, and the price projections of older papers underestimated the carbon price in 2021. Nevertheless, the results show a remarkable value for carbon sequestration in food forests per hectare, which is currently still overlooked. This valuation can be most effective in the short term by a hybrid upfront action-based and result-based payment structure (COWI & European Commision, 2021). Although more research is needed to have a comprehensive method for pricing upfront, as this study showed, possible higher sequestration can be reached in rich clay soils.

Both measurement methods and carbon certificates are in the development process. Also, extra costs might appear in the measurement and certifying of reforestation initiatives (Boosten, Martijn, & Schoonderwoerd, 2021). They also state that a substantial part of the valued CO_2 price required for monitoring and validation. Further research should therefore study the functionality of simplified methods to monitor carbon sequestration and the net profit for carbon initiatives when shifting to food forests.

Food Forestry a tool for Dutch agricultural climate goals

Food forests can be applied globally; however, in this section, the Netherlands is described. Dutch climate targets have stated a 6 Mt CO_2 reduction for the agricultural sector towards 2030 (Rijksoverheid, 2019). Moreover, the budget of reducing carbon in the Netherlands towards 2030 is 970 million euros for this reduction of 6 Mt CO_2 (Rijksoverheid, 2019), equal to 161 €/$t\ CO_2$. More specifically, the climate goals in Dutch forestry and nature management aim to sequester 0.24 Mt CO_2 in forestry by 2030 (Ministry of Agriculture, 2020). The Green Deal aims for 1000 hectares of food forests by 2030 in the Netherlands (Rijksoverheid, 2019; Ministry of Agriculture, 2020). Accordingly, if 1000 hectares store on average 4.4 $t\ C\ ha^{-1}\ yr^{-1}$ for the coming ten years, a total of 0.044 Mt C is stored, equal to 0.14 Mt $\mathrm{CO_2}$. Thus, food forests can potentially realise 50% of the forestry climate goals.

Furthermore, Dutch agriculture uses 1.8 million ha of land, of which 1 million ha is grassland (CBS, n.d.). This illustrates that food forests can reach approximately 2.3% of the agricultural climate targets with only 0.06% of agricultural land. In the longer term, if by 2050 10.000 ha consist of food forests, it might store around 1.2 Mt CO_2, which is around 20% of the agricultural climate goals of 2030. However, the carbon sequestration requires 30 years, assuming a mean sequestration of 4.4 $t\ C\ ha^{-1}\ yr^{-1}$. Still, this illustration shows that food forests may significantly contribute to reaching the climate targets, especially within the agricultural sector itself, with only a minor part of the land. Finally, it is worth noting that the SOC needs to be stable or even sequester carbon to have this amount of net sequestration.

Conclusion

This study analysed the change in carbon pools and emissions during the transition from grassland to a food forest in a chronosequence of a model food forest ecosystem on a clay soil over the first 5.5 years. This study shows strong exponential growth in aboveground carbon and a markedly different pattern in belowground carbon (SOC). Coppice is the most significant contributor in aboveground carbon at year 5.5, and the hedgerow also appears a notable source; especially in age 5.5, when they are present on all edges. In comparison, hedgerows are not present in traditional forests. Fruit and nut-bearing trees are not significant contributors until year 5.5, yet the strong exponential growth may change this outcome in the longer term. In addition, the herbaceous layer is often excluded, yet this study showed how this pool is the biggest contributor in carbon until year 4.5. Therefore, this layer needs to be included in carbon, especially for carbon certificates, comparing the results with the baseline of the grassland.

By contrast, belowground carbon shows a large variation in the SOC measurements; therefore, it remains uncertain if the soil at this stage sequestered or emitted carbon. Nevertheless, based on previous studies, positive SOC sequestration might be expected in the following ten years for (river) clay soils. However, further research is needed to test this expectation for food forests while considering the impact of raised soil. Also, it is recommended for SOC estimations to adapt the sampling depth based on the bulk density. Food forests might reach higher carbon stocks than previous studies found, as this study showed a greater sequestration rate in biomass. In addition, various factors may increase the carbon content, such as rich-carbon soils, hedgerows, and coppice species. On the other hand, the carbon flux did only find a significant difference in all CO_2; still, based on previous studies, it is expected that an annual flux analysis tends to show a reduction in all GHGs. Therefore, further research should address annual fluxes to understand the real climate mitigation potential.

In addition, further research should expand the scientific basis of carbon farming for temperate regions with variations in soil types and former land use, as this research shows the potential of storing carbon on clay soils. Former land use and soil types impact carbon pools; therefore, more replications are needed in various land use and soil types. More research is required to understand how and whether the patterns of carbon sequestration are halted in older food forests, verifying the expectations of the current bases. This research observed valuable sequestration in the above and belowground biomass; however, more research is needed to verify the cost-effectiveness and develop a standardised method for measuring carbon. The soil organic carbon measurements should be improved for understanding the net carbon sequestration in all required carbon pools. These points can support financing carbon farming in temperate regions. Besides, valuing other ecosystem services might improve seeing the entire picture regarding food forests. These recommendations will complement this study's results and open up possible opportunities for implementing food forests in the broader context in the Netherlands.

References

Baah-Acheamfour, M., Carlyle, C. N., Lim, S. S., Bork, E. W., & Chang, S. X. (2016). Forest and grassland cover types reduce net greenhouse gas emissions from agricultural soils. *Science of the Total Environment*, *571*, 1115–1127. https://doi.org/10.1016/j.scitotenv.2016.07.106

Birch, C. P. D. (1999). A new generalized logistic sigmoid growth equation compared with the Richards growth equation. *Annals of Botany*, *83*(6), 713–723. https://doi.org/10.1006/anbo.1999.0877

Björklund, J., Eksvärd, K., & Schaffer, C. (2019). Exploring the potential of edible forest gardens: experiences from a participatory action research project in Sweden. *Agroforestry Systems*, *93*(3), 1107–1118. https://doi.org/10.1007/s10457-018-0208-8

Boosten, M., Martijn, S., & Schoonderwoerd, H. (2021). *Methode voor vaststelling van emissiereductie CO2-eq*. 1–44.

Boosten, M., & Snoep, M. (2021). *Projecttype : Aanleg van nieuw bos en aanleg van boomweides en lijnvormige beplantingen buiten bosverband Inhoud*. 1–40.

Brady, N. C., & Weil, R. R. (1999). *Soil organic matter. The nature and properties of soils.* 446-490.

Brink, C., Vollebergh, H. R. J., & van der Werf, E. (2016). Carbon pricing in the EU: Evaluation of different EU ETS reform options. *Energy Policy*, *97*, 603–617. https://doi.org/10.1016/j.enpol.2016.07.023

Buinink, K. (2020). *Assessment on the variation in aboveground carbon stock of dutch food forests*.

Cairns, M. A., Brown, D., Helmer, E. H., & Baumgardner, G. A. (1997). <Cairns1997Oecologia-root-biomass-allocation.pdf>. *Oecologia*, *111*, 1–11.

CBS. (n.d.). StatLine - Emissies broeikasgassen (IPCC); klimaatsector, kwartaal. Retrieved June 14, 2021, from https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84979NED/table?ts=1623654174990

CLO. (n.d.). Land- en tuinbouw: ruimtelijke spreiding, grondgebruik en aantal bedrijven, 1980-2018 | Compendium voor de Leefomgeving. Retrieved May 4, 2021, from https://www.clo.nl/indicatoren/nl211908-agrarisch-grondgebruik-

Collier, S. M., Ruark, M. D., Oates, L. G., Jokela, W. E., & Dell, C. J. (2014). Measurement of greenhouse gas flux from agricultural soils using static chambers. *Journal of Visualized Experiments*, (90), 1–8. https://doi.org/10.3791/52110

ConvertUntis. (2021). Molecular weight and molar mass for chemistry problems. Retrieved August 9, 2021, from https://www.convertunits.com/molarmass/

COWI, & European Commision. (2021). *Operationalising an EU carbon farming initiative Executive summary*.

COWI, Institute Ecological, & IEEEP. (2021). Annexes to Technical Guidance Handbook - setting up and implementing result-based carbon farming mechanisms in the EU. In *Report to the European Commission, DG Climate Action on Contract No. CLIMA/C.3/ETU/2018/007. COWI, Kongens Lyngby*.

den Herder, M., Moreno, G., Mosquera-Losada, R. M., Palma, J. H. N., Sidiropoulou, A., Santiago Freijanes, J. J., … Burgess, P. J. (2017). Current extent and stratification of agroforestry in the European Union. *Agriculture, Ecosystems and Environment*, *241*, 121–132. https://doi.org/10.1016/j.agee.2017.03.005

Deng, L., Zhu, G. yu, Tang, Z. sheng, & Shangguan, Z. ping. (2016). Global patterns of the effects of land-use changes on soil carbon stocks. *Global Ecology and Conservation*, *5*, 127–138. https://doi.org/10.1016/j.gecco.2015.12.004

Directplant. (n.d.). Meidoornhaag (Crataegus monogyna). Retrieved July 28, 2021, from https://www.directplant.nl/meidoornhaag-crataegus-monogyna.html

Drost, S., & Bodelier, P. (2017). *Soil Greenhouse gas flux measurements in the field*.

Erkman, S. (1997). Industrial ecology: An historical view. *Journal of Cleaner Production*, *5*(1–2), 1–10. https://doi.org/10.1016/s0959-6526(97)00003-6

European Commission. (2021). New EU Forest Strategy for 2030. *Angewandte Chemie International Edition, 6(11), 951–952.*

Foley, J. A. (2011). Can we feed the world & sustain the planet? *Scientific American*, *305*(5), 60–65. https://doi.org/10.1038/scientificamerican1111-60

Green Deal voedselbossen. (n.d.). Program national monitoring program food forest. Retrieved April 29, 2021, from https://www.greendealvoedselbossen.nl/nationaal-monitoringsprogramma-voedselbossen-nmvb/

Grosjean, G., Fuss, S., Koch, N., Bodirsky, B. L., De Cara, S., & Acworth, W. (2018). Options to overcome the barriers to pricing European agricultural emissions. *Climate Policy*, *18*(2), 151–169. https://doi.org/10.1080/14693062.2016.1258630

Hairiah, K., van Noordwijk, M., Sari, R. R., Saputra, D. D., Widianto, Suprayogo, D., … Gusli, S. (2020). Soil carbon stocks in Indonesian (agro) forest transitions: Compaction conceals lower carbon concentrations in standard accounting. *Agriculture, Ecosystems and Environment*, *294*(August 2019), 106879. https://doi.org/10.1016/j.agee.2020.106879

Hein, L., Remme, R. P., Schenau, S., Bogaart, P. W., Lof, M. E., & Horlings, E. (2020). Ecosystem accounting in the Netherlands. *Ecosystem Services*, *44*(May 2019), 101118. https://doi.org/10.1016/j.ecoser.2020.101118

Huppes, G., & Ishikawa, M. (2011). Visions for Industrial Ecology. *Journal of Industrial Ecology*, *15*(5), 641–642. https://doi.org/10.1111/j.1530-9290.2011.00385.x

ICRAF. (n.d.). ICRAF Database - Wood Density. Retrieved June 13, 2021, from http://db.worldagroforestry.org//wd

IGRAC. (n.d.). Drought in the Netherlands and its impact on groundwater resources | International Groundwater Resources Assessment Centre. Retrieved July 29, 2021, from https://www.un-igrac.org/stories/drought-netherlands-and-its-impact-groundwater-resources

IPCC. (2013). Climate Change 2013 The Physical Science Basis. In *Researchgate.Net*. Retrieved from https://www.researchgate.net/profile/Abha_Chhabra2/publication/271702872_Carbon_and_Other_Biogeochemical_Cycles/links/54cf9ce80cf24601c094a45e/Carbon-and-Other-Biogeochemical-Cycles.pdf

Jónsson, T. H., & Snorrason, A. (2018). Single tree aboveground biomass models for native birch in Iceland. *Icelandic Agricultural Sciences*, *31*(1), 65–80. https://doi.org/10.16886/IAS.2018.05

Kaufman, S. M. (2012). Quantifying sustainability: Industrial ecology, materials flow and life cycle analysis. *Metropolitan Sustainability: Understanding and Improving the Urban Environment*, 40–54. https://doi.org/10.1533/9780857096463.1.40

Kay, S., Rega, C., Moreno, G., den Herder, M., Palma, J. H. N., Borek, R., … Herzog, F. (2019). Agroforestry creates carbon sinks whilst enhancing the environment in agricultural landscapes in Europe. *Land Use Policy*, *83*(March), 581–593. https://doi.org/10.1016/j.landusepol.2019.02.025

KNMI. (n.d.). KNMI - Recente droogtes in historisch perspectief. Retrieved July 29, 2021, from https://www.knmi.nl/over-het-knmi/nieuws/recente-droogtes-in-historisch-perspectief

Lehmann, L. M., Lysák, M., Schafer, L., & Henriksen, C. B. (2019). Quantification of the understorey contribution to carbon storage in a peri-urban temperate food forest. *Urban Forestry and Urban Greening*, *45*(May), 126359. https://doi.org/10.1016/j.ufug.2019.06.002

Lesschen, J. P., Heesmans, H., Mol-dijkstra, J., Doorn, A. Van, & Verkaik, E. (2012). *Mogelijkheden voor koolstofvastlegging in de Nederlandse landbouw en natuur*. 62.

Lim, T. S., & Loh, W. Y. (1996). A comparison of tests of equality of variances. *Computational Statistics and Data Analysis*, *22*(3), 287–301. https://doi.org/10.1016/0167-9473(95)00054-2

Limareva, A. (2014). *Ecological Principles in Natural Temperate Forest Ecosystems Relevant for Productive Food Forests*. *1*, 123.

Lucas-Moffat, A. M., Huth, V., Augustin, J., Brümmer, C., Herbst, M., & Kutsch, W. L. (2018). Towards pairing plot and field scale measurements in managed ecosystems: Using eddy covariance to cross-validate CO2 fluxes modeled from manual chamber campaigns. *Agricultural and Forest Meteorology*, *256–257*(August 2016), 362–378. https://doi.org/10.1016/j.agrformet.2018.01.023

Malhi, Y., Baldocchi, D. D., & Jarvis, P. G. (1999). The carbon balance of tropical, temperate and boreal forests. *Plant, Cell and Environment*, *22*(6), 715–740. https://doi.org/10.1046/j.1365-3040.1999.00453.x

Manley, J., Kooten, G. C. Van, & Moeltner, K. (2003). *Resource and Environmental economics and Policy Analysis (REPA) Research Group Department of Economics University of Victoria Creating Carbon Offsets in Agriculture through No-Till Cultivation : A Meta-Analysis of Costs and Carbon Benefits*.

Meredith, S. (2021). Why Europe’s carbon market is experiencing a boom like never before. Retrieved August 11, 2021, from https://www.cnbc.com/2021/05/18/why-europes-carbon-market-is-experiencing-a-boom-like-never-before.html

Milne, E., & Ehqhàwv, D. Q. G. H. (n.d.). *The benefits of soil carbon*.

Ministry of Agriculture. (2020). *Bos voor de toekomst*.

Montagnini, F., & Nair, P. K. R. (2004). Quaternary codes and biphase sequences from Z8-codes. *Problemy Peredachi Informatsii*, *40*(2), 50–62. https://doi.org/10.1023/B

Mosquera-Losada, M. R., Santiago-Freijanes, J. J., Rois-Díaz, M., Moreno, G., den Herder, M., Aldrey-Vázquez, J. A., … Rigueiro-Rodríguez, A. (2018). Agroforestry in Europe: A land management policy tool to combat climate change. *Land Use Policy*, *78*(May), 603–613. https://doi.org/10.1016/j.landusepol.2018.06.052

Muukkonen, P., Picea, Á., & Pinus, Á. (2007). *Generalized allometric volume and biomass equations for some tree species in Europe*. 157–166. https://doi.org/10.1007/s10342-007-0168-4

Neeff, T. (2021). What is the risk of overestimating emission reductions from forests – and what can be done about it? *Climatic Change*, *166*(1–2), 1–19. https://doi.org/10.1007/s10584-021-03079-z

OECD. (2021). Effective Carbon Rates 2021. *Effective Carbon Rates 2021*. https://doi.org/10.1787/0e8e24f5-en

Otieno, K., Onim, J. F. M., Bryant, M. J., & Dzowela, B. H. (1991). The relation between biomass yield and linear measures of growth in Sesbania sesban in western Kenya. *Agroforestry Systems*, *13*(2), 131–141. https://doi.org/10.1007/BF00140237

Pandey, D., Agrawal, M., & Pandey, J. S. (2011). Carbon footprint: Current methods of estimation. *Environmental Monitoring and Assessment*, *178*(1–4), 135–160. https://doi.org/10.1007/s10661-010-1678-y

Petrone, R. M., Chasmer, L., Hopkinson, C., Silins, U., Landhäusser, S. M., Kljun, N., & Devito, K. J. (2014). Effects of harvesting and drought on CO2and H2o fluxes in an aspen-dominated western boreal plain forest: Early chronosequence recovery. *Canadian Journal of Forest Research*, *45*(1), 87–100. https://doi.org/10.1139/cjfr-2014-0253

Poeplau, C., Don, A., Vesterdal, L., Leifeld, J., Van Wesemael, B., Schumacher, J., & Gensior, A. (2011). Temporal dynamics of soil organic carbon after land-use change in the temperate zone - carbon response functions as a model approach. *Global Change Biology*, *17*(7), 2415–2427. https://doi.org/10.1111/j.1365-2486.2011.02408.x

Pribyl, D. W. (2010). A critical review of the conventional SOC to SOM conversion factor. *Geoderma*, *156*(3–4), 75–83. https://doi.org/10.1016/j.geoderma.2010.02.003

Ravindranath, H., & Ostwald, M. (2008). *Carbon Inventory Methods: Handbook for Greenhouse Gas Inventory, Carbon Mitigation and Roundwood Production Projects*.

Reijneveld, A., van Wensem, J., & Oenema, O. (2009). Soil organic carbon contents of agricultural land in the Netherlands between 1984 and 2004. *Geoderma*, *152*(3–4), 231–238. https://doi.org/10.1016/j.geoderma.2009.06.007

Rijksoverheid. (2019). Klimaatakkoord. *Klimaatakkoord*, 250. Retrieved from https://www.klimaatakkoord.nl/binaries/klimaatakkoord/documenten/publicaties/2019/06/28/klimaatakkoord/klimaatakkoord.pdf

Ruehlmann, J., & Körschens, M. (2009). Calculating the Effect of Soil Organic Matter Concentration on Soil Bulk Density. *Soil Science Society of America Journal*, *73*(3), 876–885. https://doi.org/10.2136/sssaj2007.0149

Rytter, R. M. (2012). The potential of willow and poplar plantations as carbon sinks in Sweden. *Biomass and Bioenergy*, *36*, 86–95. https://doi.org/10.1016/j.biombioe.2011.10.012

Rytter, R. M., Rytter, L., & Högbom, L. (2015). Carbon sequestration in willow (Salix spp.) plantations on former arable land estimated by repeated field sampling and C budget calculation. *Biomass and Bioenergy*, *83*, 483–492. https://doi.org/10.1016/j.biombioe.2015.10.009

Sakin, E., Deliboran, A., & Tutar, E. (2011). Bulk density of harran plain soils in relation to other soil properties. *African Journal of Agricultural Research*, *6*(7), 1750–1757. https://doi.org/10.5897/AJAR10.502

Sandbag Climate Campaign CIC. (n.d.). Carbon Price Viewer - Ember. Retrieved June 14, 2021, from https://ember-climate.org/data/carbon-price-viewer/

Schafer, L. J., Lysák, M., & Henriksen, C. B. (2019). Tree layer carbon stock quantification in a temperate food forest: A peri-urban polyculture case study. *Urban Forestry and Urban Greening*, *45*(June 2018), 126466. https://doi.org/10.1016/j.ufug.2019.126466

Schenau, S., Berkel, J. Van, Bogaart, P., Driessen, C., Horlings, E., & Wur, M. L. (2021). *Natuurlijk Kapitaalrekeningen*.

Seasonal Gardening. (n.d.). Crataegus (Hawthorn) Trees for UK Gardens. Retrieved July 28, 2021, from https://www.seasonalgardening.co.uk/trees/crataegus.asp

Soussana, J.-F., Soussana, J.-F., Loiseau, P., Vuichard, N., Ceschia, E., Balesdent, J., … Arrouays, D. (2004). Carbon cycling and sequestration opportunities in temperate grasslands. *Soil Use and Management*, *20*(2), 219–230. https://doi.org/10.1079/sum2003234

Templer, P. H., Pinder, R. W., & Goodale, C. L. (2012). Effects of nitrogen deposition on greenhouse-gas fluxes for forests and grasslands of North America. *Frontiers in Ecology and the Environment*, *10*(10), 547–553. https://doi.org/10.1890/120055

The World Bank. (2021). Carbon Pricing Dashboard | Up-to-date overview of carbon pricing initiatives. Retrieved June 17, 2021, from https://carbonpricingdashboard.worldbank.org/map_data

Toensmeier, E. (2016). The Carbon Farming Solution: A Global Toolkit of Perennial Crops and Regenerative Agriculture practices for Climate Change Mitigation and Food Security.

Torralba, M., Fagerholm, N., Burgess, P. J., Moreno, G., & Plieninger, T. (2016). Do European agroforestry systems enhance biodiversity and ecosystem services? A meta-analysis. *Agriculture, Ecosystems and Environment*, *230*(August), 150–161. https://doi.org/10.1016/j.agee.2016.06.002

Trottier, S., Boudreau-sannier, V., Qa, A., Brander, M., & Tipper, R. (2015). Understanding the Changes to Global Warming Potential (GWP) Values Climate Change Analyst. *Ecometrica*, *February*.

UNFCCC. (2013). *Methodological tool Estimation of carbon stocks and change in carbon stocks of trees and shrubs in A / R CDM project activities Version 04.2*. 32. Retrieved from https://cdm.unfccc.int/methodologies/ARmethodologies/tools/ar-am-tool-14-v4.2.pdf

Van Dam, M., Bongiorno, G., & Veen, C. (2021). *From grassland to food forest : impact of land-use transition on microbial communities and nutrient cycling*. (April), 1–49.

van Huissteden, J., van den Bos, R., & Marticorena Alvarez, I. (2006). Modelling the effect of water-table management on CO2 and CH4 fluxes from peat soils. *Geologie En Mijnbouw/Netherlands Journal of Geosciences*, *85*(1), 3–18. https://doi.org/10.1017/S0016774600021399

von Wuehlisch, G. (2011). *Evidence for Nitrogen Fixation in the Salicaceae Family*. *38*(March), 80–83.

Weidema, B. P., Thrane, M., Christensen, P., Schmidt, J., & Løkke, S. (2008). Carbon footprint: A catalyst for life cycle assessment? *Journal of Industrial Ecology*, *12*(1), 3–6. https://doi.org/10.1111/j.1530-9290.2008.00005.x

Appendix

Appendix A Measurement of aboveground biomass

Appendix A.1 Measurement of the litter layer

Step 1. Land use category or project activity

The land-use category under study is a (food) forests, which exists of five plots with different plantation periods and a baseline plot which is grassland. The former land use type was grassland. The project activity is reforestation from grazed/agricultural grassland to forests used for food production. This case study has no use of fertilisers and irrigation, also no rotational crops, although some trees are planted after the beginning phase.

Step 2. Project boundary and map

The project boundaries are illustrated below (Fig. 1). As can been seen, the plots are located next to each other. Also, it is worthwhile to note that plot B is not rectangular due to the low density on the left side, and another coppice experiment. Therefore, only the plot within the orange placeholder is selected.

Step 3. Stratify the project area

NMPFF and earlier soil research already investigated the area. Therefore, I decided to use the same locations, as this makes it more coherent. Within the litter measurement, the most usual spots are chosen. Thus, spots with trees or shrubs or massive amount of litter were excluded.

Step 4. Select the plot method.

Five plots are located in the various plots (Fig. 1)

Step 5. Select carbon pools and measurements.

The carbon pools selected for this carbon estimation for aboveground: litter, grass, shrubs, trees (e.g. coppice, fruit and nut bearing trees), and for belowground: belowground biomass and SOC (soil). The litter layer was measured half in March.

Step 6. Identify key parameters

For the non-woody species the key parameters to be recorded are Density, Fresh weight of herb layer and dry weight of herb layer.

Step 7. Select sampling method and plot size.

The plot size is for the non-woody species was of 0.5m x 0.5m. Thirty plots in total may be too large for the a 1 m2 harvesting method, because this will not fit in the ovens and destroys more surface on the food forest, thus a ¼ m2 plots is used.

Step 8. Prepare the fieldwork and the data recording.

The fieldwork was prepared by building a bamboo frame. This made the harvesting measurement more accurate. Paper bags were used for the collection. Additionally, tools were provided by LekkerLandGoed.

Step 9. Sampling design - Step 10. Locate and lay sample plots.

The locations were retrieved from C. van der Veen and I. van der Zanden. These locations were gathered in one overview. See: https://goo.gl/maps/snExNF5r7ifvvKex6

Step 11. Measure the indicator parameters in the field

The measurement was performed by marking the locations and racking the dead grass (litter) by hand (Fig. 11,12). The living grass stayed on the locaties as visible. As this measurement was done half March, there was only little grass.

Figure 11 (left): The ¼ M2 plot including litter; Figure 12 (right): plot after harvesting litter

Step 12. Record and compile data

The bags were weighted beforehand and afterwards dried in the oven of 40 degrees Celsius for seven days.

Finally, the weighted litter was converted to carbon, which is 47% of the total dried Biomass.(Ravindranath & Ostwald, 2008)

Step 13. Analyse data and uncertainty.

Accordingly, the average of the five were scaled to one hectare, which will be used in the data analysis of the report. The uncertainty is plotted by error bars, showing the standard deviation.

Figure 13 : The bags of litter in the oven;

Appendix A.2 Measurement of grass production

Step 1. Land use category or project activity

The land-use category under study is a (food) forests, which exists of five plots with different plantation periods and a baseline plot which is a grassland. The former land use type was grassland. The project activity is an reforestation from grazed/agricultural grassland to forests used for food production. This case study has no-use of fertilisers and irrigation, also no rotational crops, although some trees are planted after the beginning phase.

Step 2. Project boundary and map

The project boundaries are illustrated below (Fig. 1). As can been seen, the plots are located next to each other. Also, its worthwhile to note that plot B is not rectangular, due to the low density on the left side, and another coppice experiment. Therefore, only the plot within the orange placeholder is selected.

Step 3. Stratify the project area

The trees that were already planted before switching to a food forests are out of the plots. This makes the trees near the waterline, which are located underneath plot B and between plot D and A2 (fig 14) out of scope. In short, only trees planted by LekkerLandGoed were included. Besides, all trees within the plots were measured.

Step 4. Select the plot method.

Five plots are located in the various plots (Fig. 1)

Step 5. Select carbon pools and measurements.

The carbon pools selected for this carbon estimation for aboveground: litter, grass, shrubs, trees (e.g. coppice, fruit and nut bearing trees), and for belowground: belowground biomass and SOC (soil). The grass layer was measured half in April and half in May.

Step 6. Identify key parameters

For the non-woody species the key parameters to be recorded are Density, Fresh weight of herb layer and dry weight of herb layer.

Step 7. Select sampling method and plot size.

The same plot size is used for the non-woody species, which was of 0.5m x 0.5m. Thirty plots in total may be too large for the a 1 m2 harvesting method, because this will not fit in the ovens and destroys more surface on the food forest, thus a ¼ m2 plots is used.

Step 8. Prepare the fieldwork and the data recording.

The fieldwork was prepared by building a bamboo frame. This made the harvesting measurement more accurate. Paper bags were used for the collection. Additionally, tools were provided by LekkerLandGoed.

Step 9. Sampling design - Step 10. Locate and lay sample plots.

The locations were retrieved from C. van der Veen and I. van der Zanden. These locations were gathered in one overview. See: https://goo.gl/maps/snExNF5r7ifvvKex6

Step 11. Measure the indicator parameters in the field

The measurement was performed by marking the locations and harvesting the grass (Fig. 14,15).


Figure 14 (left): The ¼ M2 plot including litter; Figure 15 (right): plot after harvesting litter

Step 12. Record and compile data

The bags were weighted beforehand and afterwards dried in the oven at 40 degrees Celsius for seven days.

Finally, the weighted grass was converted to carbon, which is 47% of the total dried Biomass.(Ravindranath & Ostwald, 2008)

Step 13. Analyse data and uncertainty.

Accordingly, the average of the five were scaled to one hectare, which will be used in the data analysis of the report. The uncertainty is plotted by error bars, showing the standard deviation.

Appendix A.3 Measurement of woody species

Step 1. Land use category or project activity

The land-use category under study is a (food) forests, which exists of five plots with different plantation periods and a baseline plot which is a grassland. The former land use type was grassland. The project activity is an reforestation from grazed/agricultural grassland to forests used for food production. This case study has no-use of fertilisers and irrigation, also no rotational crops, although some trees are planted after the beginning phase.

Step 2. Project boundary and map

The project boundaries are illustrated below (Fig. 14). As can been seen, the plots are located next to each other. Also, its worthwhile to note that plot B is not rectangular, due to the low density on the left side, and another coppice experiment. Therefore, only the plot within the orange placeholder is selected.

Step 3. Stratify the project area

The trees that were already planted before switching to a food forests are out of the plots. This makes the trees near the waterline, which are located underneath plot B and between plot D and A2 (fig 14) out of scope. In short, only trees planted by LekkerLandGoed were included. Besides, all trees within the plots were measured.

Step 4. Select the plot method.

Each plot was completely measured within the orange boxes (Fig. 14).

Step 5. Select carbon pools and measurements.

The carbon pools selected for this carbon estimation for aboveground: litter, grass, shrubs, trees (e.g. coppice, fruit and nut bearing trees), and for belowground: belowground biomass and SOC (soil). The woody species were measured between March and May 2021]

Step 6. Identify key parameters

For the woody species these were diameter at knee height (DKH) (converted to diameter at breast height (DBH), the height (measured for a subset to generate an allometric equation), and the species.

For the non-woody species, this was dry weight, and size of the plot.

Step 7. Select sampling method and plot size.

As previously stated, the plot size is for the woody species the total area (Fig. 14). This improves the accuracy of the plot method.

Step 8. Prepare the fieldwork and the data recording.

Various tools were used for the fieldwork, which are: slide callipers (measuring DKH and DBH), measuring tape (5m), fine measuring tape (measuring large amounts of DKH), inclinometer app, and a data recording sheet.

Step 9. Sampling design - Step 10. Locate and lay sample plots.

The whole plots were measured, these were identified and labelled accordingly. First these were marked at a hard-copy paper, and consequently these were digitalised in the QGIS program.

Step 11. Measure the indicator parameters in the field

The remaining trees are measured on all the plots (see fig. 17), the species are identified, mostly Populus and Salix species. In this research is chosen to measure the trees at diameter at knee height (DKH), because due to the age gradient within this forest some trees are not height enough for a breast height (130 cm).

Figure 17. Measuring aboveground biomass in LekkerLandGoed at DKH (60 cm above ground).

Step 12. Record and compile data

All the trees were digitalised in excel and QGIS, which were used for the calculations.

Step 13. Analyse data and uncertainty.

First of all, the allometric equation were analysed, which is stated in the method section. Accordingly, these equations were used to calculate the carbon from the measured diameters. All the trees were estimated and categorised based on the age (see materials and method section).

Appendix B: method emissions

Procedure retrieved from (Drost & Bodelier, 2017, p1-4)

"

1. Install the rings in the flux chambers at least a day before in the field to prevent disturbance before measuring GHG fluxes.
2. Install the batteries on top of the chambers. **Make sure that the ventilator inside is working!!!!**
3. Put one thermometer inside the ring and one outside.
4. Put the Flux chamber on the ring, place septum in front to make measurements easier.
5. Register the flux chamber number on the GHG data file (example APPENDIX 1).
6. Put a flux cover (made from isolation foil) over the chamber (if dark chamber are used to prevent higher temperatures inside than outside the chamber)
7. Take an air sample (50ml) close to the chamber, this is your T0 sample with the syringe and needle.
8. Put the sample in the vial (which already has one needle pushed through the septum for flushing), flush the vial with 44ml of the sample and put the rest of it (6ml) in the vial. However, for analyses on the GC as well as to prevent contamination, we need an overpressure of 1 bar in the vials. Therefore, before filling in the last 6ml the outlet needle has to be removed from the container. Than the 6ml can be pushed into the container.
9. Register the time on the GHG data file.
10. If measuring more chambers at once: continue with the other plots with step 5-7. It is possible to handle 8 flux chambers at the same time
11. Take air sample from the flux chambers after 20 (T1), 40 (T2), 60 (T3), 75 (T4) and 90 (T5) minutes similar as step 9-10 in different vials. For each measurement, you will need 6 vials.
12. After completed the measurements, remove the flux chamber and the thermometers. Write down the temperature inside and outside the chamber (used to determine differences that could cause over- or under-pressure).
13. You will measure the samples on the auto sampler on the GC. Depending on the GHG fluxes interested in, use the following GCs:
    a. CO_2: Trace-ultra: possible to measure low and high concentrations
    b. N_2O: Trace 1300
    c. CH_4: Trace-ultra: possible to measure high concentrations, Trace 1300 for measurements below 10 ppm
    d. All three GHG gasses at or below atmospheric levels: Trace 1300

"

Appendix C: Pictures illustrating differences in the plots