Aboveground carbon stock and soil properties of Dutch food forests: trends and connections

Rosalba Hendriks

Major Research Project

Master *Environmental Biology: Ecology & Natural Resource Management*

Academic supervisor: Dr. Pita Verweij
Daily supervisor: Bastiaan Rooduijn
Second corrector: Heitor Mancini Teixeira

This research was conducted in collaboration with the *Nationaal Monitoringsprogramma Voedselbossen,* part of the *Green Deal Voedselbossen*.

Universiteit Utrecht

Nationaal Monitoringsprogramma Voedselbossen

Green Deal Voedselbossen

/ Acknowledgements // dankbetuigingen

Eline Disselhorst, ik weet dat jij bij jouw dankwoord eindigde met de mensen die je het meest dierbaar zijn, maar bij mij is de volgorde precies omgekeerd 😉 Nu ben je mijn beste vriendin in Utrecht, maar ik heb je eerst leren kennen als een enthousiaste, doorpakkende en pragmatisch denkende veldwerkpartner. Of het nou weer of geen weer was, honger of dorst, niks hield jou tegen. Je was mijn steun en toeverlaat in het bodemonderzoek en ik denk niet dat ik me een betere collega had kunnen wensen.

Rintje Frankena, nadat ik drie gezellige maanden met Eline in het veld erop had zitten, was het spannend of mijn volgende veldwerkpartner ook zo'n goede collega zou zijn. Gelukkig is dat helemaal goed gekomen! Ik vond het ontzettend fijn hoe enthousiast je meedeed met het opmeten van de bovengrondse koolstofopslag, en dat je open stond voor het veldwerk. Bovendien waren de filosofische gesprekken altijd top en was je er altijd om me te herinneren in welke jaszak ik m'n autosleutel gestopt had. Hopelijk blijf je nog lang van me verliezen met Risk zodat we vaak met Eline en Ruud spelletjes moeten blijven spelen.

Bastiaan Rooduijn, ik heb met bewondering gekeken naar je toewijding en kennis op het gebied van voedselbosbouw. Jouw ideeën en inzicht, en het voorwerk dat je voor het NMVB hebt opgezet zijn van cruciaal belang geweest voor mijn onderzoek. Ook vind ik het mooi hoe je de menselijke kant van het werk benadrukt, en ik vond de veldbezoeken dan ook erg gezellig. Ik heb erg veel geleerd van mijn tijd bij het NMVB, en ik hoop dat mijn onderzoek heeft bijgedragen aan de toekomst van voedselbossen, waar jij en vele anderen zich zo hard voor inzetten.

Pita Verweij, ik wil je graag bedanken voor de hartelijke begeleiding en voor het vertrouwen dat je in me hebt gehad, ook wanneer ik dat zelf niet had. Dankzij jouw ervaring en gedegen onderzoeksachtergrond heeft dit major research project richting gekregen en kon ik concreet met de data aan de slag. Je flexibiliteit in de begeleiding heeft me in staat gesteld om mijn reis naar Colombia op orde te krijgen, waar ik erg dankbaar voor ben.

Gerard Korthals, wat heb je je vol enthousiasme ingezet voor het aaltjesonderzoek! Hoewel ik je interessante bevindingen helaas niet meer mee kon nemen in mijn werk, ben ik zeer onder de indruk van alles wat jullie hebben gedaan. Bedankt voor je optimisme en energie.

Bram Wendel, bedankt voor al het werk dat je doet voor het NMVB, en voor het meedenken over mijn lenteprotocollen. Dankzij jou zijn de windhagen dit jaar meegenomen in het onderzoek, en dat bleek een schot in de roos! Hopelijk blijf je met veel plezier je inzetten voor voedselbosonderzoek.

Heitor Mancini Teixeira, I am very grateful to have you as my second corrector. You are always happy to help and have really assisted me with some important details of my statistical analyses, as well as given Rintje and me the confidence and tools to conduct the carbon stock assessments properly. I hope that the Dutch food forests will continue to interest you, because a researcher like you who combines statistical knowledge with practical insights is of great value to the budding research on temperate European agroforestry.

Mijn vader, Paul Hendriks. Wat was het leuk om na al die jaren van mee het veld in gaan voor jouw werk, jou nu ook mee te nemen naar mijn eigen onderzoek! Dankjewel dat je ons uit de brand hebt geholpen, zowel door bij te springen als door me een spoedcursus boomherkenning te geven. Deze is zeker van pas gekomen en ik kijk er naar uit om samen te blijven leren over de natuur.

Kaspar Buinink voor het delen van je ruwe data, bevindingen en het meedenken over mijn onderzoek! Ik hoop dat je dit onderzoek ziet als een goede voortzetting van de waardevolle meetreeks die je bent gestart.

Isabelle van der Zande, bedankt voor je enthousiasme en het meedenken in de vroege fase van het bodemveldwerk. En natuurlijk bedankt dat we je bulk density ringen zo lang mochten lenen!

Mijn vriend Ruud Schrijver, dankjewel voor alle Excel-ondersteuning, dubbelchecken van mijn berekeningen, en bedankt dat ik de auto zo vaak mocht lenen! En dat je alle aarde en blaadjes in de auto en het huis hebt getolereerd. Maar bovenal: dankjewel voor het feit dat je mijn steun en toeverlaat bent geweest, en zo vaak hebt gekookt als ik laat terug kwam van veldonderzoek.

Bas Lerink, bedankt voor het meedenken over de berekeningsmodellen voor de bovengrondse koolstofopslag. Al heb ik gekozen te blijven bij de modellen van Kaspar, je input was zeer waardevol en gaf me meer vertrouwen in mijn berekeningen.

Loet Paulussen, wat ontzettend tof dat je verder bent gegaan met het onderzoeken van de houtige soorten in voedselbossen! Je bent een echte strijder en hebt al veel hordes overwonnen bij je veldwerk. Ga zo door, ik kan niet wachten om je resultaten te zien.

Mitsubishi Spacestar, je bent al oud en binnenkort kom je niet meer door de APK. MAAR je bent voor altijd mijn favoriete auto. Zonder jou hadden we de bemonsteringen nooit op tijd rond gekregen!

Alle voedselboseigenaren en beheerders van het NMVB, graag zou ik iedereen individueel bedanken, maar dan zou dit dankwoord even lang worden als het verslag zelf! Daarom wil ik hierbij mijn dank uitspreken voor jullie flexibiliteit, enthousiasme, voor alle goede gesprekken, zelfgemaakte cake, hulp bij het bemonsteren, en vooral de steun bij het determineren van bomen en struiken, zowel fysiek als door het doorsturen van aanplantkaarten. Bedankt voor jullie vertrouwen en steun, ik hoop dat ik in de vorm van dit verslag iets terug heb kunnen doen!

/ Abstract

Agroforestry as an alternative to intensive agricultural systems is increasing in popularity in the Netherlands. However, due to the lack of research on agroforestry systems development in the Dutch situation, it is difficult to assess the potential for upscaling and development trajectory of food forests. In order to monitor food forests in the Netherlands, the Nationaal Monitoringsprogramma Voedselbossen (NMVB) was created. Within the NMVB, this major research project has for the first time explored the relations between aboveground carbon (AGC) stock of woody species and belowground parameters. AGC stock, hedgerow AGC stock, species density of woody species, soil organic carbon (SOC), plant-available macronutrients, CEC and earthworm count were measured and analyzed in respectively all 33 (belowground variables) or a selection of 22 food forests (aboveground variables).

AGC stock followed a near-exponential growth curve after 5 years of age, which differs from the sigmoid curve found earlier for Dutch food forest AGC stock. However, much like the earlier found trend this projection is uncertain due to the low number of old food forests. Hedgerow AGC stock per ha was 12 to 6000 times higher than the AGC stock per ha of the parcel itself. SOC was not correlated with AGC and compaction did not result in significant variation in SOC data. Belowground variables differed significantly across dominant soil types, but were not correlated to food forest age. Aboveground variables were correlated to age, and variation in AGC stock was weakly linked to dominant soil type. However, due to the small population of food forests and the uneven distribution according to soil type and age, drawing conclusions is complicated. A most significant model of soil type, age and plant available sodium explained approx. 80% of the variation in AGC stock. Plant available Na-content in the soil was negatively correlated to the size of AGC stock.

As most belowground variables were not significantly related to AGC stock, the data suggests that changes in belowground variables are much slower in comparison to aboveground variables. Literature on belowground development of agroforestry systems suggests that aboveground vegetation does have an effect on belowground processes. Continued monitoring of belowground variables in relation to AGC stock is therefore advised, but significant relations may not become apparent in the first decade or two.

/ Lekensamenvatting // Dutch Layman Summary

De gevolgen van grootschalige intensieve landbouw beginnen steeds beter merkbaar te worden in Nederland. Door monocultuur (het verbouwen van één enkel gewas en het verdelgen van al het andere (planten)leven) en het overmatig gebruik van bemesting komen het landbouw-ecosysteem en de voedselzekerheid onder druk te staan. In de zoektocht naar een meer natuur-inclusief landbouwsysteem wordt er steeds meer gekeken naar voedselbosbouw als een natuurvriendelijker alternatief. Een voedselbos is een landbouwsysteem dat voor een groot deel bestaat uit meerjarige planten, waaronder bomen en struiken, en gebaseerd is op de ecologie van een bos. Bij voedselbosbouw worden verschillende soorten gewassen en niet-productieve planten gecombineerd, zodat iedere functie binnen een ecosysteem vervuld kan worden. Dit zorgt voor een grotere biodiversiteit en een bodemleven dat robuuster is.

Voedselbosbouw is een systeem van landbouw dat al sinds mensenheugenis wordt gebruikt. Het is echter in gematigde klimaten steeds zeldzamer geworden, sinds vooruitgang in technologie mensen in staat heeft gesteld om intensievere landbouw te bedrijven. De meeste voedselbos-systemen vindt men tegenwoordig in de Tropen, waar een systeem met hogere biodiversiteit voor de lokale bevolking vaak nog rendabel is. Hierdoor is de meeste moderne kennis over voedselbosbouw gebaseerd op onderzoek in tropische gebieden, zoals Midden-Amerika en Afrika. Nu voedselbosbouw in Nederland in opkomst is, is het belangrijk dat er hier onderzoek wordt gedaan naar het ontwikkelingstraject van voedselbossen. Dit zorgt ervoor dat managers van voedselbossen gerichter te werk kunnen gaan met kennis gebaseerd op de Nederlandse situatie, en dat er een beter beeld is van de mogelijke functie van voedselbosbouw binnen de landbouw in Nederland.

Om gestructureerd onderzoek naar Nederlandse voedselbosbouw te faciliteren, is het Nationaal Monitoringsprogramma Voedselbossen (NMVB) opgericht. Binnen het NMVB zijn studentenonderzoeken gedaan naar zowel boven- als ondergrondse aspecten van het voedselbossysteem. Er zijn echter nog geen studies gedaan die een verband proberen te leggen tussen het bodemsysteem en bovengrondse uitkomsten, zoals opbrengst of groei van het bos. Omdat het ecosysteem van een voedselbos zo complex is, is het lastig om interacties aan te tonen. Wel kan het vinden van indicatoren van bovengrondse groei nuttig zijn voor het indirect managen van de groei van het bovengrondse voedselbos. Daarom heb ik ervoor gekozen om mijn onderzoeksstage binnen het NMVB te focussen op de ontwikkeling van bovengrondse biomassa en bodemeigenschappen in de tijd, en de relatie tussen beide.

Als voornaamste bovengrondse variabele heb ik de bovengrondse koolstofopslag (BKO) in houtige soorten (bomen en struiken) van voedselbossen onderzocht. Planten halen netto kooldioxide uit de lucht en leggen de koolstof uit deze verbinding vast in hun weefsels. Het verminderen van het broeikasgas kooldioxide in de atmosfeer helpt klimaatverandering tegen te gaan. Daarnaast is de toename van koolstofopslag een indirecte indicatie van groei van de planten in het bos: deze nemen immers kooldioxide uit de lucht op om te kunnen groeien. Het meten van de BKO is dus nuttig zowel voor het inschatten van de rol die voedselbossen kunnen spelen bij het tegengaan van klimaatverandering, als voor het meten van de groei van voedselbossen door de tijd heen.

Om te kijken welke aspecten van het voedselbos een rol kunnen spelen in de groei van de BKO, heb ik gekeken naar verschillende eigenschappen van de bodem, en naar biodiversiteit van de bomen en struiken. Voor het berekenen van de koolstofopslag was het bepalen van de soort van de boom of struik nodig. Deze verzamelde gegevens konden meteen ingezet worden om de soortdichtheid (aantal soorten per m^2) te bepalen. De bodemvariabelen die onderzocht waren, zijn: ondergrondse organische koolstofopslag (OKO), concentraties van plant-beschikbare macronutriënten, kationenuitwisselingscapaciteit (CEC) van de bodem, en aantal wormen.

Het verzamelen van de data voor dit onderzoek vond plaats tijdens twee veldwerkperiodes. In de winter van 2021-2022 vond het grootste gedeelte van de bodembemonstering plaats. Deze metingen zijn gedaan bij alle 33 bossen die aangesloten waren bij het NMVB. In de lente van 2022 zijn de metingen gedaan voor het schatten van de bovengrondse koolstofopslag, bij een selectie van 22 van de 33 bossen.

Bij de bodemonderzoeken werden aardwormen geteld in een uitgestoken kubus van 20x20x20 cm bodem, op drie tot zes punten per voedselbos. Op deze zelfde punten werd een dichtheidsring gebruikt om een grondstaal uit te nemen. Deze ring heeft een vaste inhoud, waardoor de dichtheid van de grond berekend kon worden nadat deze gedroogd was. In combinatie met analyse van organische koolstofgehalte van de bodem, kon de OKO berekend worden. Op 15 tot 30 punten per voedselbos werd de compactie (=samendrukking) van de bodem gemeten met een penetrometer. Op deze zelfde punten werd met een guts een staal van 25 cm grond genomen. Een deel van het mengsel van alle stalen per voedselbos werd opgestuurd naar het laboratorium van Eurofins Agro in Wageningen voor analyse van de bodemeigenschappen (o.a. macronutriënten en CEC).

Tijdens het lenteveldwerk werd de BKO opgemeten, in 3 tot 6 plots van 10x10 meter per voedselbos. Hiertoe werden alle houtige planten (bomen en struiken) opgemeten met een hoogte van minstens 1,30 m en een omtrek op borsthoogte (vastgesteld op 1.30 m) van minimaal 5 millimeter. Van elke individuele stam van een boom of struik werden de hoogte en omtrek genoteerd, en het individu werd gedetermineerd (=op soort gebracht). Verder werden in elk bos de windhagen apart opgemeten, indien aanwezig. Een windhaag is een beschermende singel van snelgroeiende, wind verdragende bomen en struiken die dikwijls wordt aangeplant om een landbouwperceel te beschermen tegen de invloed van de elementen.

De groei van de BKO van voedselbossen over tijd laat een semi-exponentiële trend zien vanaf de leeftijd van 5 jaar. Eerdere berekeningen voorspelden dat de groei van BKO in

Nederlandse voedselbossen rond 20 jaar leeftijd afgevlakt en de trendlijn voor de groei zou S-vormig zijn, maar deze nieuwe gegevens laten zien dat het aannemelijk is dat de afname van de groei nog niet in zicht is voor de Nederlandse situatie. Verder werd er omgerekend veel meer bovengrondse koolstof per hectare aangetroffen in de windhagen dan op het voedselbosperceel zelf. Dit betekent dat wanneer de windhagen niet meegenomen worden in een koolstofberekening, er een belangrijk deel van de daadwerkelijk aanwezige koolstof over het hoofd wordt gezien. De verwachting is dat dit vooral het geval is voor jonge bossen, omdat de soorten die in windhagen worden gebruikt doorgaans veel sneller groeien dan de soorten die voor productie worden aangeplant in het voedselbos.

Statistische analyse van de individuele variabelen laat zien dat de onderzochte bovengrondse eigenschappen (BKO en SD) vooral sterk verband houden met de leeftijd van het bos, en dat de ondergrondse eigenschappen (OKO, concentraties van plant-beschikbare macronutriënten, CEC van de bodem, en aantal wormen) vooral sterk verband houden met het dominante bodemtype van het bos (klei, leem of zand). Deze bevindingen duiden erop dat bovengrondse en ondergrondse processen in een voedselbos op een andere tijdschaal verlopen. Onderzoek naar oudere voedselbossen in het buitenland laat zien dat voedselbosbouw wel degelijk een effect heeft op de samenstelling van de bodem; hier gaat echter veel meer tijd overheen dan het geval is voor bovengrondse groei.

Door middel van statistische toetsing is gezocht naar het beste model om variatie in BKO te verklaren aan de hand van de onderzochte variabelen. Het model dat het meest accuraat was, liet zien dat een combinatie van leeftijd, bodemtype en plant-beschikbare natrium 79% van de variatie in BKO verklaarde. Vooral interessant is het feit dat natrium een rol speelt in dit model. Natrium had een negatieve relatie tot BKO (oftewel, een hogere concentratie natrium kwam overeen met een lagere hoeveelheid BKO), wat correspondeert met de literatuur. Kleine hoeveelheden natrium zijn essentieel voor het functioneren van veel planten, maar bij een hoge concentratie natrium treedt voor de meeste planten vergiftiging op. Doordat het natriumgehalte van de Nederlandse bodem dreigt toe te nemen door verzilting, is het essentieel voor Nederlandse voedselbosbouwers in de kustgebieden om maatregelen te treffen om het natriumgehalte in het bos laag te houden, om een snellere aanwas van bomen en struiken te garanderen.

Net als eerder onderzoek naar bovengrondse koolstofopslag in voedselbossen, laat dit onderzoek weer zien dat er veel potentie zit in voedselbossen als CO_2-reducerend landbouwsysteem. Wel zorgt de kleine dataset van beschikbare bossen, en de lage leeftijd van de meeste Nederlandse voedselbossen, voor een uitdaging bij het formuleren van robuuste conclusies over de interacties tussen voedselbosbouw en de bodemkwaliteit. Ondanks deze beperkingen vormt dit onderzoek een belangrijke basis voor verdere monitoring van voedselbossen door de jaren heen. Met het klimmen van de jaren zullen de waarde van de data en statistische kracht van de relaties alleen maar toenemen, en ik kan niet wachten om de rapporten te lezen van de studenten die na mij zullen komen.

/ Table of Contents

/ 1. Introduction

The Earth's ecological health and human food security are under pressure due to intensive farming practices. One of the alternative food production systems available to decrease environmental impact is agroforesty.
Agroforestry can be generally defined as "a dynamic, ecologically based, natural resource management system that, through the integration of trees on farms and in the agricultural landscape, diversifies and sustains production for increased social, economic and environmental benefits for land users at all levels" (*FAO, 2015*). Under this broad definition, agroforestry practices date back to early human civilization (*King, 1987*). Especially in the Earth's tropical regions, mixed production systems in a (semi)natural habitat setting have been a prevailing agricultural strategy (*Atangana et. al., 2014*).

In temperate regions, mixed cropping and silvopastures have been historically part of agricultural activities (*Herzog et. al., 1998 ; Dupraz et. al., 2018 ; Newman et. al., 2018*). However, agroforestry practices have been replaced by more intensive tilling as agrotechnology improved in industrialized countries (*Dupraz et. al., 2018*). In recent decades, growing awareness of the environmental degradation caused by intensive agriculture has led to an increased interest in sustainable farming methods (*Dupraz et. al., 2018 ; Herzog, 1998 ; Gatzweiler, 2003*). This has led to a recent surge in interest in agroforestry, especially in North America and more recently in Europe (*Dupraz et. al., 2018 ; Herzog, 1998*).

In The Netherlands, intensive agriculture has led to a stark decline in biodiversity and degradation of soil ecosystems, including excessive nitrogen concentrations (*Keijzers, 2000 ; Stokstad et. al., 2019 ; Korevaar, 1992*). Increased EU-wide pressure to tackle environmental decline has increased societal interest and public spending on agroforestry in the past years (*Santiago-Freijanes, 2018 ; Mosquera-Losada, 2016*).

Public funds have facilitated a rapid increase in food forests but knowledge on actual agroforestry production systems in the Dutch context is lacking (*Green Deal Voedselbossen, 2017*). In order to create a structured network of pioneering food forests and increase understanding of agroforestry practices, the 'Green Deal Voedselbossen' was signed in 2017 (*Green Deal Voedselbossen, 2017*).

Within this interdisciplinary cooperation, the 'Nationaal Monitoringsprogramma Voedselbossen' (NMVB) was created. The NMVB facilitates research on participating food forests by linking students and senior researchers to their 33 affiliated food forests (*NMVB, 2022*). While agroforestry is a broadly used term, participating production systems are identified as 'food forest' specifically according to the following definition:

"human-designed productive ecosystem modeled after natural forests, of which parts serve the purpose of human consumption. Food forests contain a canopy of higher trees, at least three other vegetation strata (lower trees, shrubs, herbs, groundcover plants, underground plants and creepers), and a rich forest soil ecosystem" (translated from *Green Deal Voedselbossen, 2017*).

Within the NMVB, research has been done on a variety of aboveground and belowground variables relevant to food forest development (*NMVB, 2022*). However, no studies have yet been conducted that attempt to link aboveground variables to a variety of soil characteristics.
Due to the complexity of the agroforestry system, interactions between aboveground and belowground properties are yet poorly understood (*Cardinael et. al., 2020*). Still, an exploration of possible correlations between aboveground and belowground effects can benefit food forest managers. Furthermore, a more holistic understanding of how agroforestry promotes changes in aboveground and belowground parameters may be useful for communication to the public at large, and to contribute to a better understanding of the possible costs and benefits of food forests specifically in the Netherlands.

Carbon sequestration is a very relevant topic to food forest management, not only due to the environmental benefits of mitigating atmospheric CO_2, but also economically (*Nath et. al., 2015 ; Meena et. al., 2022*).
The sale of carbon credits, although a dividing topic within the agroforestry community, has been pushed as a means to gain additional income for starting food forests in the investment phase (*Meena et. al.,2022 ; Schoeneberger, 2009 ; Montagnini & Nair, 2004*).
Therefore, being able to reliably project aboveground carbon stock growth can be beneficial for food forest managers seeking to receive financial benefits from external parties for biomass growth, alongside ecological benefits. Reliability of research results also depends on a representative sampling of the researched system; due to the heterogeneity of food forests, it is important to consider which elements of a forest may need to be assessed individually in order to capture the complete picture of carbon storage.

This major research project has been conducted to investigate tentative connections between aboveground carbon stock and multiple belowground parameters, as well as generating data on the development of pioneering food forests over time. In this study, I also seek to expand on the existing carbon stock assessments within the NMVB by introducing assessments of hedgerows, which can increase accuracy of carbon stock assessment and investigate the potential of hedgerows as early carbon capturers.
The study has been based on the following research questions, to which the respective hypotheses are formulated:

1.1 Research questions and hypotheses

Can belowground parameters and woody species density explain variation in Dutch food forest aboveground carbon stock, and does the inclusion of hedgerow measurements improve the quality of aboveground carbon stock estimations?

Sub questions:

1. What is the actual aboveground carbon stock of woody species in Dutch food forests? And how does this compare to baseline measurements from 2020?

I hypothesize that the aboveground carbon stock in all measured food forests will have seen a significant increase from the baseline measurement of 2020. I also expect the inclusion of the oldest Dutch food forest 'Nij Boelens' and some younger forests to generate a more diverse carbon stock dataset.

2. What is the estimated hedgerow aboveground carbon stock in selected food forests with hedgerows? How does this compare to the estimated carbon stock in the inner part of the food forest?

I hypothesize that more carbon is stored in hedgerows than in the inner part of the food forest in most forests, but that the importance of hedgerows will diminish with increasing food forest age.

3. Is there a trend over time in the concentrations of soil macronutrients, soil organic carbon stock, worm count, species density and CEC in the database?

I hypothesize that soil macronutrients, worm count, species density and CEC will not show correlations with age, as soil development in temperate zones take longer to recover from intensive use than the age of most of the sampled food forests. Furthermore, I think that soil organic carbon stock will increase significantly with forest age.

4. Do the concentrations of macronutrients, soil organic carbon stock, worm count, species density and CEC vary across soil types?

I hypothesize that all variables differ between soil types, with the exception of species density, because the latter is highly reliant on human interference

5. Which combination of potential explanatory variables (soil variables, biodiversity, and food forest age) can best explain the variation in aboveground carbon stock?

I hypothesize that the best predicting model of aboveground carbon stock will be based on soil organic carbon stock, soil type and food forest age, or, minimally, at least soil type and food forest age. Furthermore, I expect age to have the strongest predicting value within the model.

/ 2. Theory

2.1 Aboveground carbon stock

Aboveground carbon (AGC) stock in a non-climatic natural forest increases over time (*Vierling et. al., 2008*). The accumulation of natural forest AGC approximates an S-curve, with sequestration slowing down as the forest grows (*Asner et.al.,2018, Granata et. al., 2016*). For agroforestry in temperate regions, first results suggest similar growth patterns (*Feliciano et. al., 2018*). However, due to the scarcity of older, well-documented food forests, it is difficult to ascertain a trend in current temperate food forests (*Schafer et. al., 2019, Feliciano et. al., 2018*).

First research results in Dutch food forests suggest that AGC accumulation may slow down after approximately 20 years, but the dataset is too small to provide a robust conclusion (*Buinink, 2020*).

2.2 Hedgerow carbon stock

Hedgerows, borders of woody vegetation planted to serve as a natural barrier or protection against the elements, have been part of the temperate culture landscape since the Neolithic era (*Edmonds, 1999*).

While the proliferation of thousands of kilometers of hedgerows is mostly associated with the British culture landscape, worldwide agroforestry systems, including in tropical zones, are increasingly based on hedgerow plantation principles (*Rao, Nair, Ong, 1997, Pattanayak & Mercer, 1998*). Although crop yield increases and soil improvement qualities of hedgerows are estimated to be much higher in temperate agroforestry systems than in tropical ones, hedgerow structures have a positive impact on biodiversity and aboveground carbon sequestration in both contexts (*Rao, Nair, Ong, 1997 ; Drexler, Gensior, Don, 2021*).

In temperate agroforestry systems, the potential for additional aboveground carbon storage is especially large for hedgerows bordering young or open production systems (*Drexler, Gensior, Don, 2021 ; Golicz et. al., 2021 ; Carswell et. al., 2009*). Research in the food forest 'Lekker Landgoed' in Haarzuilens confirmed these findings of increased carbon storage for the Dutch food forest situation, and highlighted the need for investigation into the hedgerow carbon stock of other food forests affiliated with the NMVB (*Wendel, 2019*).

2.3 Belowground soil organic carbon stock

The soil organic carbon content (SOC) is to some degree plastic and reactive to environmental changes (*Gingrich et. al., 2007*). Agricultural activity is known to impact soil carbon stocks, with more intensified agricultural systems leading to the strongest decrease in carbon stock (*Guo et. al., 2002*). Reforestation positively impacts soil carbon stock in the first decades after restoration (*Jones et. al., 2019 ; Risch et. al., 2008*). In established secondary forests and silvopastures, accumulation of SOC with age is limited, and soil nutrients are more determinant of changes of SOC stock (*Jones et. al., 2019 ; Cardinael et. al., 2017*).

Assessments of carbon stock of food forests are scarce, but some studies have been done on SOC stocks in agroforestry systems, especially in the tropical setting (*Ramos et. al., 2018*). Within this setting, agroforestry systems reportedly had a higher SOC stock compared to other agricultural land uses, with outcomes being heavily influenced by management and biodiversity of the plantation (*Murthy et. al., 2013 ; Manaye et. al., 2021; De Beenhouwer, 2016*).

2.4 Species density

Species density is defined as the amount of unique species per area of measurement (*Lomolino, 2001*). For trees, an increase in species density was shown to be correlated with an increase in number of trees within a forest system (*Wills et. al., 1997*). Furthermore, an increasing number of studies suggests that mixed species forestry systems can over-yield systems low in species density (*Pretzsch et. al., 2015*). Although it remains unknown what factors contribute to this effect in specific situations, increased tree species density has been linked to lower pathogen spread, higher stand density due to differences in species growth patterns, and a decrease in microbial stratification (*Wills et. al., 1997 ; Pretzsch & Schütze, 2015 ; Pretzsch & Biber, 2016 ; Lejon et. al., 2005*). Positive effects of woody species density have also been identified in agroforestry-specific contexts (*Fifanou et. al., 2011*). Aboveground and soil carbon sequestration have been shown to increase with species density in multiple studies on agroforestry systems (*Nair et. al., 2010 ; Islam et. al., 2015 ; Saha et. al., 2009*).

2.5 Soil macronutrients and cation exchange capacity

Plants are dependent on soil macronutrients for survival and growth (*Tripathi et. al., 2014*). While specific needs vary between species, plants need the presence of all these elements to perform vital functions (*Maathuis, 2009*). A distinction is made between primary soil macronutrients (nitrogen, phosphorus, potassium) and secondary soil macronutrients (calcium, magnesium, sulfur). Plants require primary macronutrients in a much larger amount than secondary macronutrients (*Mosa et. al., 2022*).
In soil macronutrient analyses, sodium is oftentimes also included in nutrient panels (*Eurofins Agro, 2022*). Sodium in large quantities is detrimental to plant development for most species, and therefore monitoring the sodium levels of the soil is important to assess soil quality for tillage (*Kronzucker et. al., 2013, Yeo & Flowers, 1983*). Furthermore, sodium in some amount is essential in plants with a C4 metabolism, and is a functional mineral in many plants in lower concentrations (*Subbarao et. al., 2003 ; Kronzucker et. al., 2013*)
While total soil stock of macronutrients provides insight into potential soil quality, not all soil macronutrient stock is directly available to plants (*Mosa et. al., 2022*). Element presence in water-soluble molecules facilitates plant availability by root uptake (*Mosa et.*

al., 2022). Assessing the stock of plant-available macronutrients provides more insight into soil suitability for plant growth *(Sinfield et. al., 2010*).

An aggregate measure of soil nutrient availability for plants is the cation exchange capacity (CEC). CEC is defined as: “a measure of the total negative charges within the soil that adsorb plant nutrient cations [...] As such, the CEC is a property of a soil that describes its capacity to supply nutrient cations to the soil solution for plant uptake” (*Leticia et. al., 2022*).

2.6 Earthworms

Earthworms (*Oligochaeta*) play a crucial role within the soil ecosystem, being known as ‘ecosystem engineers’ (*Römbke et al., 2005 ; Lavelle, 1988*). Through vertical and horizontal movements in the soil, earthworms promote a more porous soil texture, which decreases compaction and mixes soil layers, promoting easier root growth and nutrient uptake by plants (*Lowe & Butt, 2002 ; Yvan et. al., 2012*). Worms can also function as belowground seed dispersers, and increase biodiversity through predation on both soil macrofauna and plant roots (*Zirbes et. al., 2012*). Presence of earthworms has been linked to soil ecosystem health (*Fründ et. al., 2010*).

Due to their association with robust soil ecology and the relative ease with which they are counted, earthworms have been included in many surveys and layman studies (*Iannonne et. al., 2012 ; Burton et. al., 2021*). However, earthworm prevalence is correlated with soil lutum content, and earthworms generally favor clay and loam soils above sandy soils (*Lapied et. al., 2009, Römbke et. al., 2005*). Therefore, comparisons of worm count of systems on different soil types may not be productive or strongly indicative of soil health (*Fischer et. al., 2014*). In the agroforestry context, a decrease in worm count in a sandy soil system may be an indication of approximation of natural soil processes, as natural forests on sand tend to have a low worm count relative to other soil types (*Römbke, 2009 ; Muys & Lust, 1992, Alban & Berry, 1994*). This difference can be at least partially attributed to earthworm aversion to the low pH of sandy soil forests, and lower nutrient content of sand (*Baker & Whitby, 2002 ; Tripathi & Bhardwaj, 2004*).

/ 3. Materials and Methods

3.1 Sampling strategy and forest selection

A different number of forests was selected for specific parts of the data gathering for this study. Within forests, the NMVB uses standardized sampling points and plots to assure comparable databases across research projects (NMVB, 2022). These points and plots are generated using mapping and random selection features in QGIS, after which they are exported to Google Maps for use in the field (see: annex p. 60 ' GIS sample point/plot generation protocol'). More details about plot selection of the aboveground variables are given within the paragraphs of their examined variables.
For a complete list of sampled forests per variable, including forest age and soil type, see annex table 1.

Aboveground carbon (AGC) stock assessment

22 out of 33 participating forests were selected for aboveground carbon stock assessment based on historic sampling, age and dominant soil type.
In order to compare 2022 aboveground carbon stock to that of 2020, most forests selected were also part of the set of forests assessed by Kaspar Buinink and Fleur Coolen in 2020; this was the case for 18 out of 22 forests selected.

Furthermore, it was desirable to select at least 6-7 forests within each soil texture class (sand, loam and clay) to assess the influence of soil type.

One food forest was added due to its unique age: 'Nij Boelens' is a recently re-discovered food forest that represents the oldest known agroforestry system in the Netherlands. Therefore, this forest was a very interesting addition to the database.

Hedgerow carbon stock

From the food forests selected for the ACG stock assessment, all forests with hedgerows were assessed for hedgerow carbon stock. The determination of hedgerow measurement eligibility was done in the field, and depended on the following factors:

- A 'hedgerow' was defined as a consistently (generally no more than 2 meters between individual plants) planted line of woody vegetation on the border of a food forest, planted with the intent of shielding the inside of the food forest against weather influences. This definition had to be met.
- The hedgerow had to be located on the outside of the food forest, not further than 10 meters from the border of the lot (unless the outside of the lot was generally unplanted and the hedgerow was the first line of vegetation).
- At least one side of the food forest border (out of generally four sides) had to be at least 50% planted with a hedgerow.
- The hedgerow had to be part of the food forest itself, and not be either outside of the border of the forest (for example, on the other side of a bordering ditch) or be already established before the lot was destined for agroforestry.

Soil quality parameters and soil organic carbon stock

For the soil quality parameters, all 33 food forests participating in the NMVB as of November 2021 were included. Soil organic carbon stock was initially sampled in all 33 participating forests as well, but due to technical difficulties, results were only obtained from 26 out of 33 sampled forests. (*See: annex table 1*)

Worm points

Randomized sample points, called 'worm points' within the NMVB and hereafter in this report, were selected for each food forest in QGIS, following the rule of one point for every 1/3 ha of land, with a minimum of three and a maximum of six (see: annex p. x). In forests previously included in mapping by the NMVB, existing worm points were used.

Penetrometer/soil sample points

An additional set of randomized sample points for soil sampling and compaction measurements were selected for each food forest. Selection was done in QGIS, following the rule of one point for every 0.1 ha of land, with a minimum of 15 and a maximum of 30 (see: annex p. 60). In forests previously included in mapping by the NMVB, existing worm points were used.

3.2 Aboveground carbon stock assessments

3.2.1 General aboveground carbon stock assessment

Aboveground carbon stock assessment took place during the spring fieldwork period from March 2022 to May 2022. Carbon stock of woody species was measured in the field by gathering data on the height, diameter at breast height (DBH, set at 130cm) and species of each eligible specimen within 3-6 sample plots per food forest (see: sampling strategy).

Plot selection

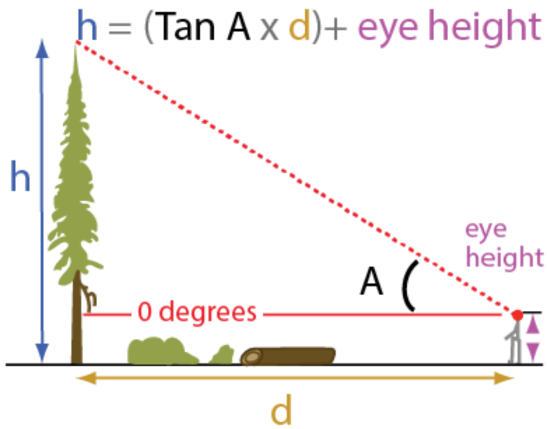
Randomized square plots of 10x10 meter were selected for each food forest in QGIS, following the rule of one plot for every 1/3 ha of land, with a minimum of three and a maximum of six (see: annex p. x). In forests previously sampled for AGC, existing plots were used where possible. If in the field it became apparent that a plot was selected on a location where a road, building or heavy groundwork such as a pond or mound had been insurrected, the plot was moved by at least 10 meters in accordance to the protocol described in annex p. x.

Woody species inclusion criteria

Eligibility was based on the criteria that a specimen be of a woody species (tree or shrub), at least 130cm in height, and have a DBH of at least 5mm. Because there was no differentiated formula used for calculating carbon stock in shrubs or trees, any offshoot from the main stem below 130cm that fit the DBH criteria was included in the measurement, irrespective of dominant growth of the specimen (shrub or tree). If the stem of a specimen fell at least partially in the sample plot, it was included.

Data gathering - specimen height and diameter

Specimen diameter was assessed using a caliper, or a soft measuring tape if the tree did not fit the latter. Height was measured either with the use of a hypsometer (model: Nikon Forestry Pro 1) or with a digital inclinometer (clinometer mobile application). The hypsometer was the preferred method of measurement, but this instrument sometimes proved unreliable in dense vegetation.
In those instances, an inclinometer was used to calculate tree height by multiplying the tangent of the angle from eye level to the top of the tree with the distance from the tree, and adding the height from ground to eye level (see image 1).



height based on distance and rotation tangent using inclinometer. Source: UBC Faculty of Forestry.

Data gathering – species identification

In the field, plant species was identified for all measured specimens. Individuals were identified at species level when possible, but if this proved impossible identification on genus level or family level was determined. The mobile applications PlantNet and rarely ObsIdentify were used to aid in identification, as well as plant data and identification in the field provided by food forest administrators or owners for many forests. Occasionally, the Heukels' Flora van Nederland (21st press, REF) was used to confirm identification.

Carbon stock calculation

The aboveground carbon stock calculations presented in this internship report are calculated according to a simplified version by Kaspar Buinink and Fleur Colen of the Verified Carbon Standard (VCS), a standard used for the certification of carbon emission reductions. The VCS has been controlled since 2005 by the non-profit organization Verra (*Verra, 2020, Buinink, 2020*).
While there are few independent reviews on the accuracy of the VCS outside of the control and research done by Verra, it remains one of the most frequently cited methods of carbon stock calculation (*Von Avenius et. al., 2018*). Furthermore, specific parts of the VCS methodologies have been verified by independent studies (*Von Avenius et. al., 2018 ; Needleman et. al., 2018 ; Sharma et. al., 2012*).
The VCS has also been used by Kaspar Buinink and Fleur Coolen in their carbon stock assessment for the NMVB in 2020, and continuation of their AGC assessment

methodology facilitates comparisons between the assessments of 2020 and 2022 (*Buinink, 2020*).

Aboveground carbon stock was calculated from the gathered measurements using the following equations:

(eq. 1) CTOT = $\frac{1}{10^6}$ * CTREE,j / A

(eq. 2) CTREE,j = BTREE,j * cf

(eq. 3) BTREE,j = V * Dwj * BEF

Where:
CTOT = amount of stored C in aboveground biomass (t C ha^{-1})

A = sample area size (m^2)

CTREE,j = amount of stored C in aboveground biomass of species j (g)

BTREE,j = aboveground tree biomass of species j (g)

cf = carbon fraction of tree biomass

V = volume of tree stem (cm^3)

Dwj = species specific wood density of species j (g cm^{-3})

BEF = biomass expansion factor

The biomass expansion factor (BEF) represents "the ratio of the total above-ground tree biomass to the biomass of the merchantable timber" (Levy, Hale and Nicoll, 2004). This factor was set at 1.15 for the equation (eq.3), which is the standard for forestry research and supported by comparative studies across species (Petersson et. al., 2012).

Species specific wood density (Dwj) takes into account the density of the wood, and therefore the carbon storage potential per volume. Species specific densities were acquired from the ICRAF global Wood Density database (*World Agroforestry, 2022*) when possible. If a species was not represented in the ICRAF compiled data, and no other reliable source of that species' wood density could be found, the average of the genus or family was take from the ICRAF database.

The carbon fraction of tree biomass (cf) was set at 0.47, which is the default carbon fraction used to describe general carbon content across tree aboveground elements, used in carbon stock research (Skog and Nicholson, 1998).

3.2.2 2020 aboveground carbon stock analysis

In order to be able to make a comparison between the current aboveground carbon stock and that of 2020, the raw data was obtained from the 2020 assessment of aboveground carbon stock of Dutch food forests by Kaspar Buinink and Fleur Colen. This raw data was filtered so that only the results were selected that fit the selection criteria of the 2022 protocol (woody species, >130 cm height, > 0.5 cm DBH). Carbon stock was calculated from this data using the same formulae as were applied to this year's aboveground carbon stock analysis.

3.2.3 Hedgerow carbon stock assessment

The assessment of hedgerow carbon stock was done simultaneously to the aboveground carbon stock assessment, on the same field days.

Plot selection

Per forest sampled for hedgerows, one to three trajectories of 5 meters were laid out along which the aboveground carbon stock of woody species was assessed. The number of trajectories depended on the number of qualifying hedgerow borders. If more than three borders of a food forest qualified as having a hedgerow, three of them were randomly selected.

Per border, the length of the hedgerow was determined in the field. In most cases, a hedgerow spanned the entire length of one border. Using a random number generator, a starting point was selected for the 5 meter trajectory. These trajectories were then marked, starting at the northwest corner of the northern border, and following the borders in a clockwise fashion.

Hedgerow carbon stock was assessed by measuring woody specimens along one to three randomly selected trajectories as described under 'sampling selection'. The same criteria for inclusion of a specimen applied to hedgerow carbon stock assessment as for the general aboveground carbon assessment (woody species, >130 cm height, >0.5 cm DBH).

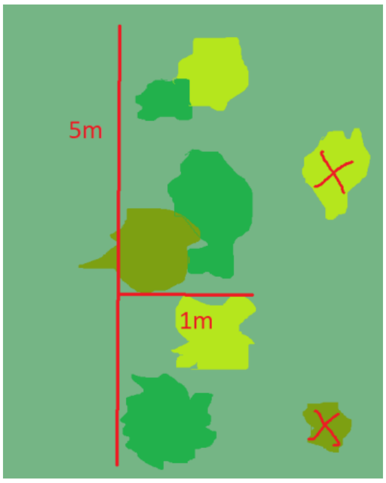


Image 1. Visualization of the limits of the hedgerow AGC trajectory plot. Made in Microsoft Paint.

Any woody specimen that grew along the 5 meter marked trajectory within a 1 meter depth range was included in the assessment (see image 1)

Carbon stock was calculated from this data using the same formulae as were applied to estimate the aboveground carbon stock of the inner part of food forests. Total hedgerow carbon stock per food forest was obtained by calculating carbon stock per meter of hedgerow and multiplying by the total length of the food forest's hedgerow(s), after which this data could be used to obtain stored carbon per ha in hedgerows, if indeed a complete ha was covered in hedgerow. This approach was taken to facilitate same-level comparisons between hedgerow and food forest body, as they are now both expressed in 'full' hectares.

3.3 Soil organic carbon stock assessment

Soil organic carbon (SOC) stock was assessed by calculating belowground carbon volume percentage based on soil bulk density and analysis of soil organic carbon content.

The assessment of soil bulk density was done partially during the winter fieldwork phase from November to January, and partially during the spring fieldwork phase from March to May. 26 of 33 participating food forests were sampled.
Bulk density of the mineral soil at surface level was measured using a bulk density ring of 8 cm in height. Therefore, only the bulk density of the top 8cm of soil was evaluated. A bulk density sample was taken at each worm point. From this sample, the dry soil weight was obtained by heating the soil samples at a temperature of …, and using the volume of the bulk density ring, soil density was calculated.

Soil organic carbon content was obtained from the soil sample analysis conducted by Eurofins (see: soil quality parameters). Multiplying the soil density (gr/ml) with the organic carbon carbon percentage yielded the volume percentage of organic carbon, which was averaged per food forest.

Soil compaction measurements

Compaction of the soil can influence SOC measurements, because it compresses soil layers which are more aerated in non-compacted soil (*Hairiah et. al., 2020*). To assess the influence of compaction on the measured SOC stock, a penetrometer was used to assess the compaction level in psi in 0-52.5 cm depth, at 7 intervals of 7.5 cm.
Penetrometer measurements were done at the 15-30 'sample/penetrometer points' for all 33 participating food forests.

3.4 Species density assessment

From the data gathered to calculate aboveground carbon stock, the species density per forest was assessed. A pivot table was made of the unique species sampled per food forest, which could then be divided by the total area sampled per forest to arrive at the species density per m^2.

3.5 Soil macronutrient concentrations and cation exchange capacity

Soil macronutrient concentrations and cation exchange capacity (CEC) were analyzed by the laboratories of Eurofins Agro, a company specialized in analysis of soil chemical and physical properties.
Samples that were sent for analysis were gathered in the winter fieldwork period from November 2021 to January 2022. Samples were gathered and analyzed for all 33 participating food forests.

For the sample gathering, a cross-section of the first 20cm of soil was taken at 15-30 'soil sample points' (see: sampling selection: penetrometer/soil sample points) using a gauge auger. These samples were mixed together in a bucket, and from this mixture two bags of 0.5 kg soil (1 kg total) were taken. Per food forest, one bag of soil sample was used for nematode analysis by the WUR (outside of this research internship), and one bag was sent to Eurofins Agro for analysis. Samples were stored at a temperature of 0-4 degrees Celsius.

The soil sample bags were analyzed by Eurofins Agro according to their 'BemestingsWijzer' soil analysis panel, which provides an overview report of soil chemical and physical qualities (Eurofins Agro).

3.6 Earthworms

During the winter fieldwork period, earthworms were counted in all 33 participating food forests. This count was done at the 'worm points' (see: sampling selection: worm points). All earthworms were counted from a cube of 20x20x20 cm (8000 cm^3) of soil, dug up at mineral soil level. No distinction was made between earthworm species or size. Number of worms per sampling plot was averaged to arrive at an average earthworm count per food forest.

3.7 Statistical analyses and data visualization

Data was stored in Excel files. Graphical and statistical data analysis were done in the statistical computing language R (R Core Team, 2019), in the integrated development environment RStudio (RStudio Team, 2019). Graphics were notably generated using the "ggplot2" package for R (H. Wickham, 2016).

Normal distribution and homoscedasticity were assessed for each statistical model. The visualizations of these assessments can be found in the Annex on pages (x-x). Log-transformation of continuous variables was first performed to attempt to meet assumptions of normality and homoscedasticity.

When appropriate, a non-parametric alternative was used for statistical tests. For a One-Way-ANOVA, the non-parametric Kruskal-Wallis test was used as an alternative. For simple regression, Spearman's rho was used as the non-parametric alternative. For generalized linear model analysis, the car package for R was used to generate additional summary statistics (Fox & Weisberg, 2019).

3.7.1 Multiple Regression Analysis of AGC

An analysis of the correlation between AGC stock and other observed variables was done, with the goal of arriving at a model which could explain the largest variation in AGC stock possible. To this end, a base generalized linear model was created, consisting of the following variables:

> *Response*: aboveground carbon stock
> *Predictors*: soil texture class, age, species density, CEC, earthworms, sand percentage of soil, lutum percentage of soil, plant-available macronutrients (counted individually)

Of these variables, only soil type was categorical, the other predictors were continuous. Due to the emphasis on continuous variables in the model, a glm was chosen over an ANCOVA model.

The summary for the model was printed, and the least significant variable was removed from the model, until the model only contained significant variables, and further reduction or alteration of the variables would lead to a decrease in significance and R^2 of the model.

To account for heteroscedasticity in the final model, a Box Cox analysis was performed to obtain the desired lambda variable for transformation to approach normality. This computation was done using the MASS package for R (Venables & Ripley, 2002). The lambda value was 0.1818182. All variables in the model were transformed using the following formula: $(x^{0.1818182} - 1) / 0.1818182$

/ 4. Results

4.1 Aboveground carbon stock

4.1.1 General aboveground carbon stock

General woody species aboveground carbon stock in the body of the food forest was assessed for 22 forests. The mean aboveground carbon stock was 9.61 Mg C per ha ± 21.56. Due to a delay in notable increase in AGC stock until after approximately 5 years, it is to be expected that the 1-sd value for this dataset exceeds the mean, as most forests are very young with only a few outliers in age producing high AGC stock values (fig. 1) One outlier that is young (3 years old), but has a high AGC stock is the food forest 'De Overtuin', which was founded in an existing arboretum (fig. 1).

Aboveground carbon stock is significantly correlated to food forest age ($p = 0.0003$), and age explains approximately 70% of variation in AGC stock (rho = 0.697).

From the fitted locally weighted smoothing trendline, a tentative exponential trend can be observed starting at the 5 year age mark (fig 2.) However, the 95% confidence interval for this trendline is quite large, and therefore a larger dataset with older forests is required to properly assess AGC stock increase trendlines for Dutch food forests (fig 2.)

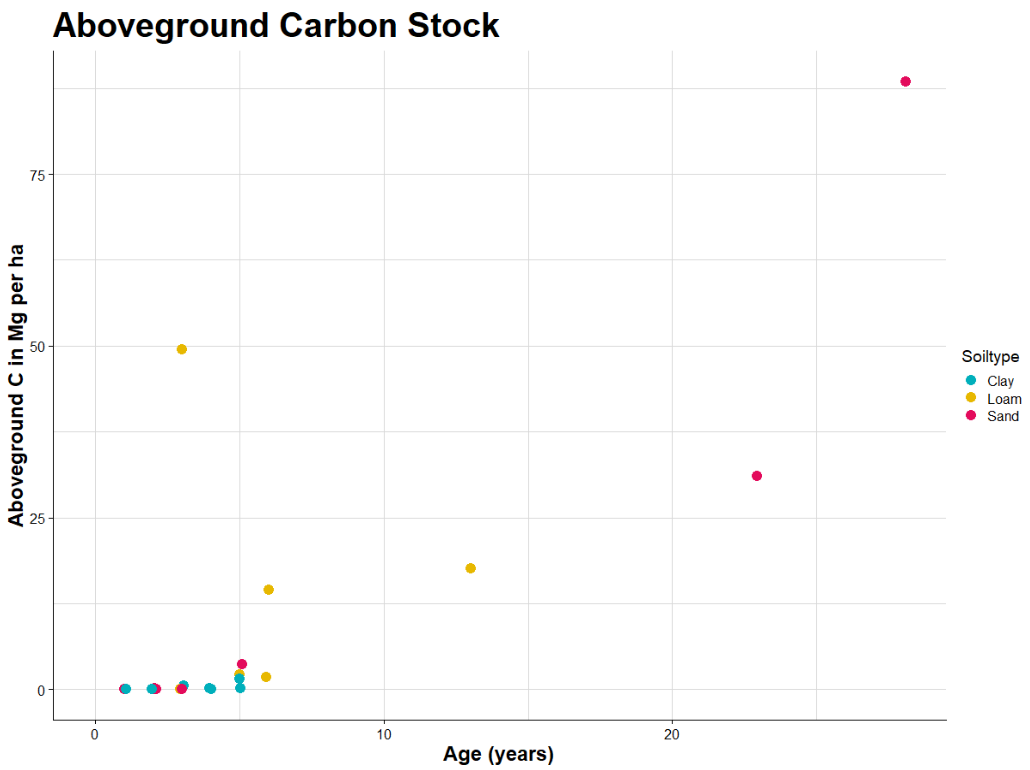


Figure 1. Time series of Aboveground carbon stock (Mg/ha). N=22. Soil type is visualized in point color; blue = clay, yellow = loam, pink = sand.

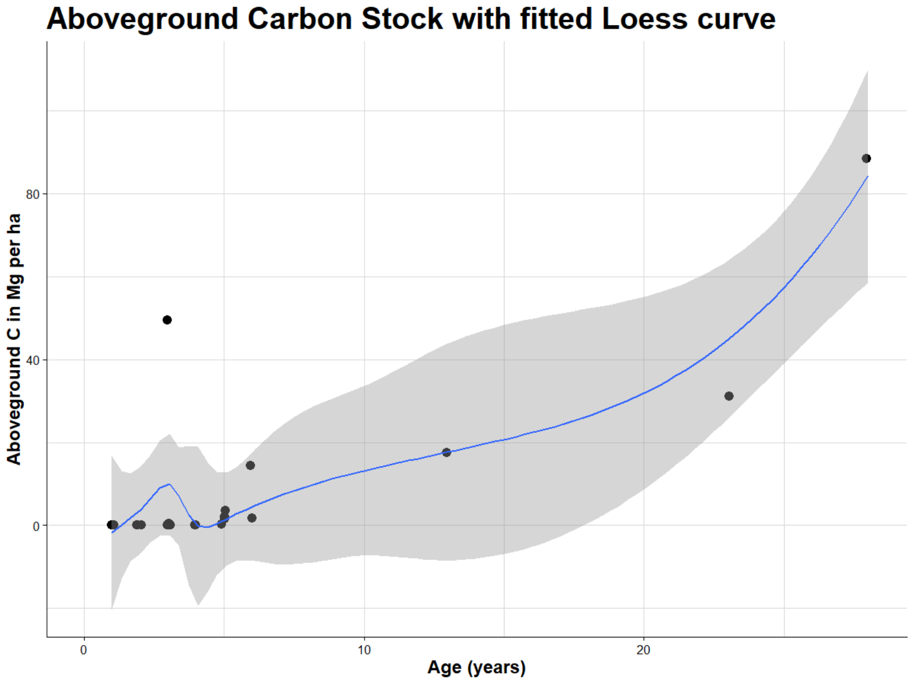


Figure 2. Time series of Aboveground carbon stock (Mg/ha) with fitted locally weighted smoothing trendline with 95% confidence interval bands. N=22. The 'bump' at the three year mark is explained by the outlier forest 'De Overtuin' (see main text).

No significant relationship was found between AGC stock and soil type (p= 0.012). However, the difference in AGC stock between clay and loam is significant (p = 0.015). (annex fig. 1)

4.1.2 Two-year carbon stock changes

The comparison of AGC in food forests sampled both in 2020 and in 2022 (n=18) is shown in Figure 3.

Figure 3. Aboveground carbon stock in 2020 (red points) related to aboveground carbon stock in 2022 (blue points). N=18. 2022 results without corresponding 2020 results are also plotted (n=4). Lines connect the respective measurements of the same forest. X axis: food forest age in years, y axis: 10log of aboveground carbon (10log Mg per ha)

There is a significant difference between the aboveground carbon stock measured in 2022, versus that of 2020 ($P < 0.0001$). There is an overall trend visible of carbon stock expansion, both on a dataset-wide chronosequence and for individual forests between the two sample periods (*fig 3.*).
However, not all forests have seen an increase in measured carbon over the past two years; seven forests have seen a decrease in carbon stock (*fig 3.*)

The most extreme outlier of this dataset in terms of AGC stock decline can be explained by looking at their specific properties. Eemvallei Zuid has very few individuals measured in both years, and the disappearance of one specimen meant that the AGC stock was immediately cut in half (*fig. 3*). Droevendaal had a lot of mounds, ditches and ponds dug in between the two years of assessment, which meant that vegetation was either removed or replanted elsewhere. Lastly, Roggebotstaete, which scores relatively 'low' with no increase in AGC stock where more increase is expected due to the woody plant mass present, has received relatively little maintenance since it has been overgrown with bramble bushes, and a lot of trees have either died or show symptoms of failure to thrive (*fig 3.*)

On average, both the increase and decrease in carbon stock is getting smaller as food forests get older (*fig. 3*). This trend is visually enhanced by the plotting on a log-scale, but in part this trend can be explained by the fact that more established forests will have a more stable AGC stock, as is found in the natural forest situation (Van Vinh et. al., 2019 ; Hudiburg et. al., 2009)

The average accumulation of AGC stock per forest per year between 2020 and 2022 was 0.377 ± 1.17 Mg per ha. However, a paired t-test shows that there is not yet a statistically significant difference in AGC stock between 2020 and 2022 ($p= 0.192$), meaning that there is a possibility that the trend in AGC increase is due to chance or other factors. Due to the general upwards trend of the 2020-2022 comparison, and the expectation that forests accumulate more carbon as they grow in the first years after planting, I suspect that the growth in AGC stock in 2 years is explainable by forest growth and not an artefact. It is important, however, that this analysis is repeated in the future when a longer chronosequence is present, and existing growth effects are more likely to become apparent from the dataset.

4.1.3 Hedgerow carbon stock

Hedgerow AGC stock was assessed for all forest within the AGC stock assessment dataset that met hedgerow requirements (n=11). Mean Hedgerow AGC was 80.23 Mg ± 162.46 per ha.

Although the dataset of 11 measured forests is very small, aboveground carbon stock in hedgerows does show a significant relationship to food forest age (p = 0.005, rho = 0.750).
Due to the small size of the dataset and the uneven distribution across soil types for the hedgerow dataset (sand=6 , loam=3 , clay=2), no statistics could be performed on the dataset using soil type as a predictor variable. However, there appears to be no significant relationship between hedgerow carbon stock and soil type (*fig 4.*). A steep linear growth in carbon stock after four years of age can be projected from the dataset, although the span and age range of forests sampled is too small to accurately predict growth patterns (*fig 5.*).

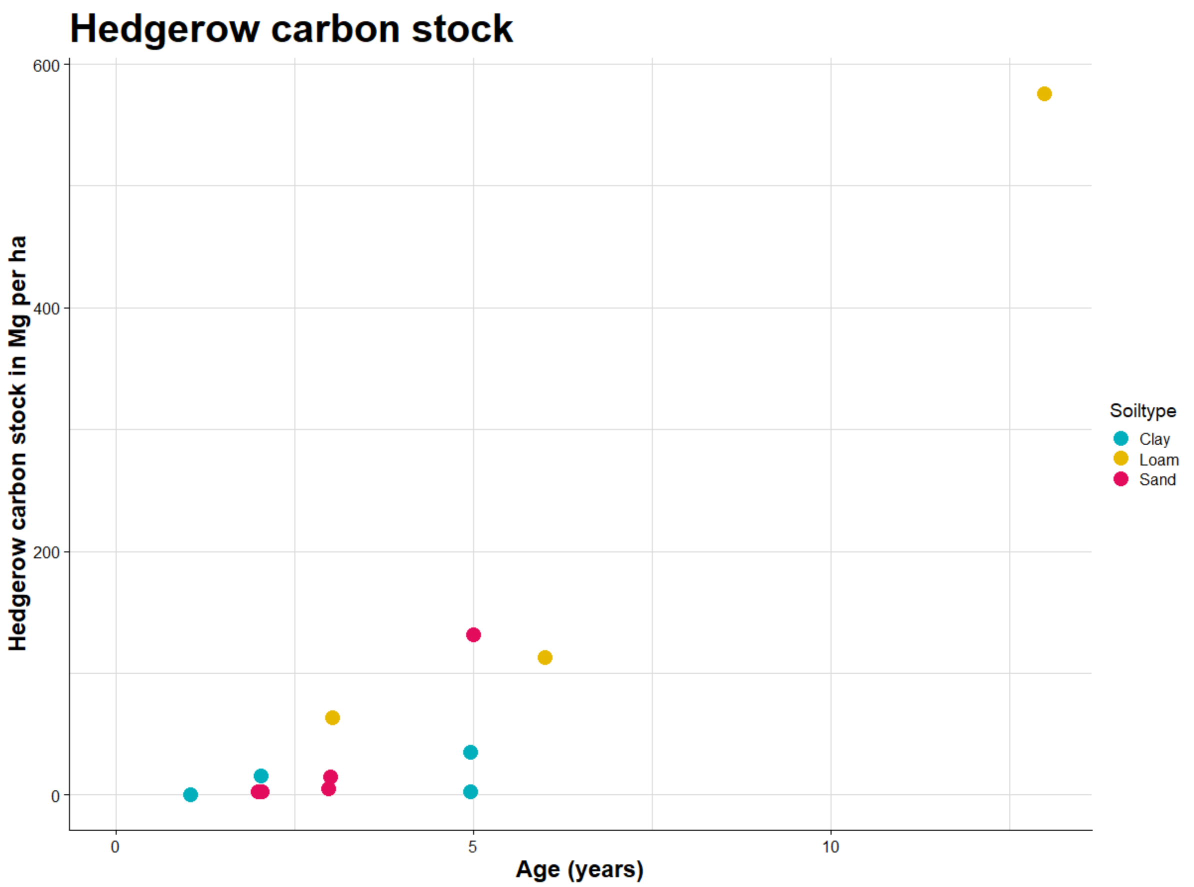


Figure 4. Time series of Hedgerow aboveground carbon stock (Mg/ha). N=11. Soil type is visualized in point color; blue = clay, yellow = loam, pink = sand. There does not appear to be a correlation between soil type and size of the HR AGC stock.

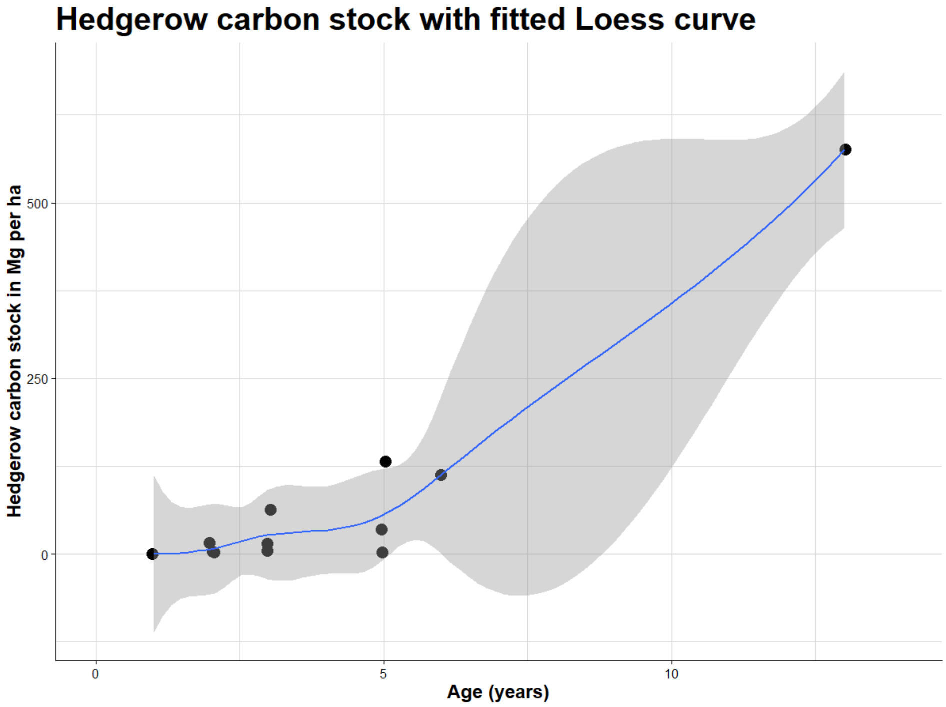


Figure 5. Time series of Aboveground carbon stock (Mg/ha) with fitted locally weighted smoothing trendline with 95% confidence interval bands. N=11.

4.2 Soil Organic Carbon stock

Belowground organic carbon stock (soil organic carbon) of the first 25cm of soil was assessed for 25 food forests. The mean SOC was 53.37 ± 21.03 Mg per ha.

No significant correlation was found between soil organic carbon stock and food forest age ($p > 0.9$, rho = 0.022). SOC stock varies strongly in the first 5 years of food forest establishment, after which it appears to decline (annex fig. 2). However, no conclusions can be drawn based on the pattern of SOC by age due to the low sample size of older food forests, and age-SOC interactions are not significant.

Soil type does not explain variation in SOC stock ($p > 0.05$). However, the p-value for this interaction is ($0.05 < p < 0.10$), which indicates a trend. This means that there is quite possibly still a noteworthy connection between SOC stock and soil type, which also becomes apparent when looking at the between-group comparison for soil types (figure x). Clay and loam do not differ significantly, while sand does from both other soil types, suggesting that the trend in SOC stock is mostly explained by sandy soils having a significantly lower SOC (figure 6.).

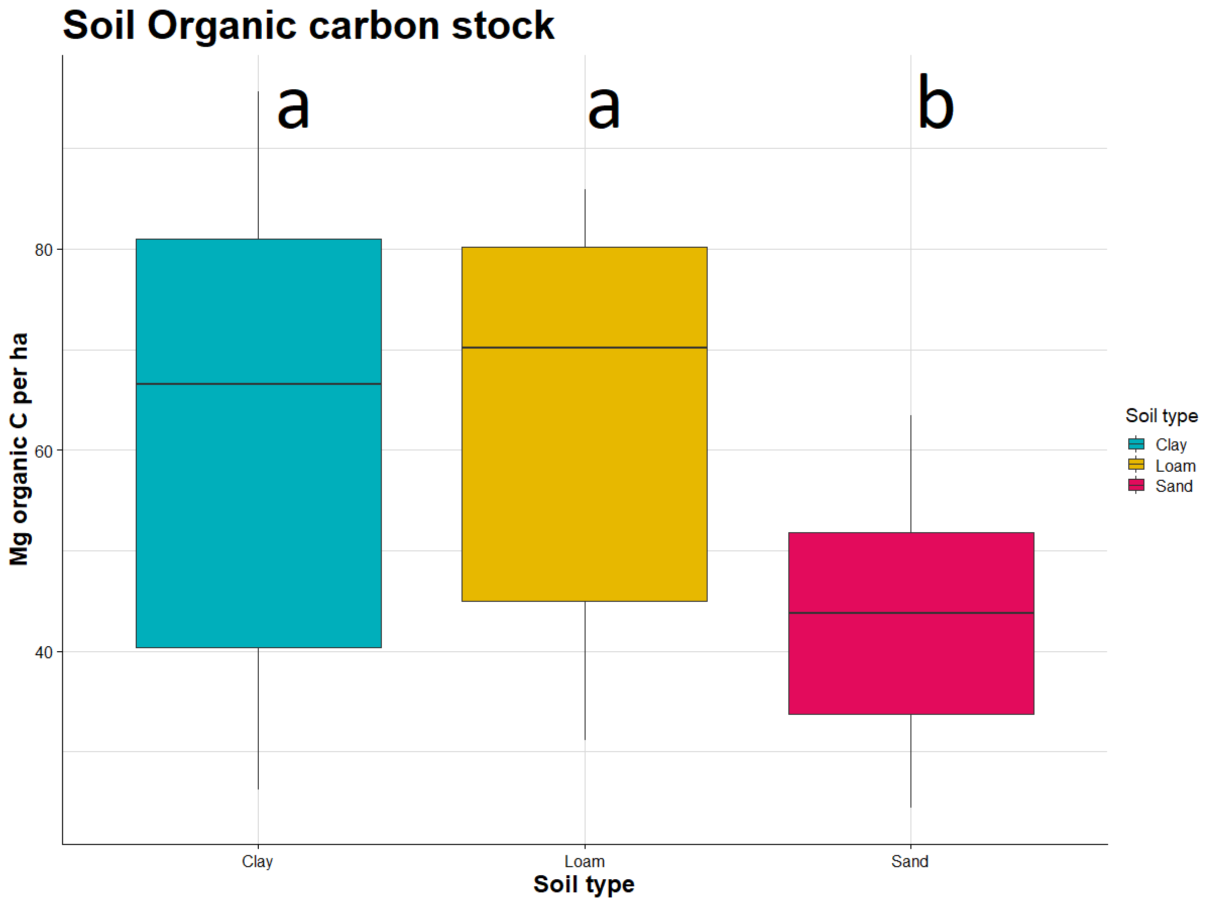


Figure 6. By-soiltype comparison of belowground organic carbon stock in 0-25cm of the soil, in Mg per ha. N=25. Blue = clay, yellow = loam, Pink = sand. Significance of soil type is an overall 'trend' at p=0.067. Clay and sand differ significantly (p=0.043), sand and loam differ significantly (p=0.040), and clay and loam do not differ significantly (p=0.991).

There is no significant relationship between average soil compaction of the top 22.5 centimeters of soil and belowground soil organic carbon at 0-25cm (p= 0.46, n=25). Soil compaction explained only slightly over 2% of variance in soil organic carbon content (Multiple R^2= 0,023; see annex table x for SOC stock and average compaction per food forest). Therefore, it is unlikely that a differences in compaction have substantially influenced the results of the SOC assessment.

There is no significant correlation between general AGC stock and SOC stock (p= 0.680, rho = 0.104, n = 18). This result is expected, because aboveground carbon stock shows a strong increase over time, while soil organic carbon stock is not significantly related to food forest age.

4.3 Species density of woody species

The average species density of woody species per m^2 sampled area was calculated for all forests of the AGC stock assessment dataset at 0.02 ± 0.018 species per m^2 (n=22).

There is a strong correlation between assessed species richness and food forest age (P 0.01060 , R^2 = 0.284). The low R^2 in combination with high significance indicates that age is a strong indicator of species density, but only explains a relatively small percentage of the variation in species density. Since most species are planted and therefore controlled by other factors than natural succession, this result is to be expected. Food forest moderators can also introduce more species over time, of course, but it was not researched during this studies what pattern culling and planting of tree species follows, and therefore it is not possible to say if there is an overlap in contribution to species density between age and food forest maintenance. Furthermore,a few high-scoring outliers make it harder to draw conclusions from the dataset (fig. 7)

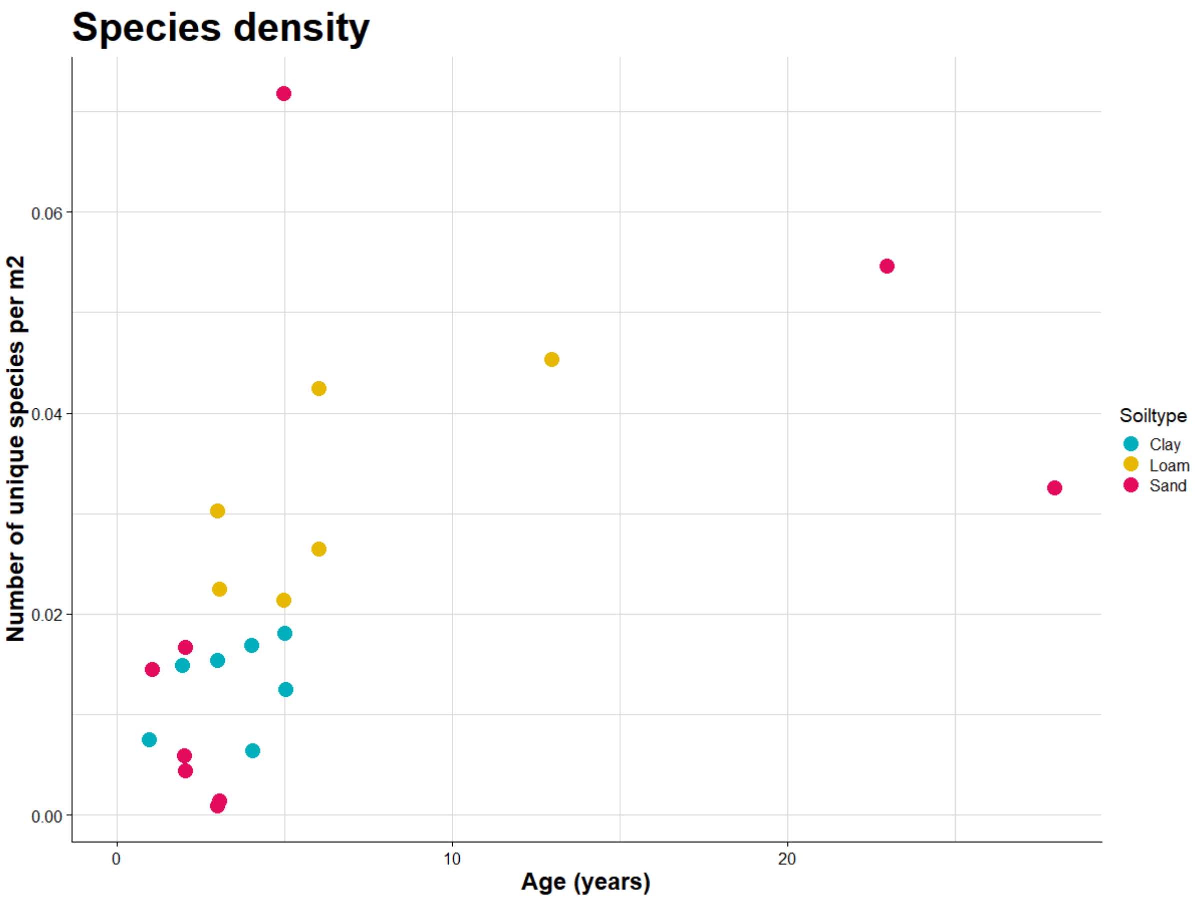


Figure 7. Time series of woody species density in species per m2. N=22. Soil type is visualized in point color; blue = clay, yellow = loam, pink = sand.

There was no significant relation between species density and food forest soil type.Between soil types, species density only differed significantly between clay and loam, at P = 0.005 (*annex fig. 3*). Forests on sand show a larger variation in species density than clay and loam (*annex fig. 3*)

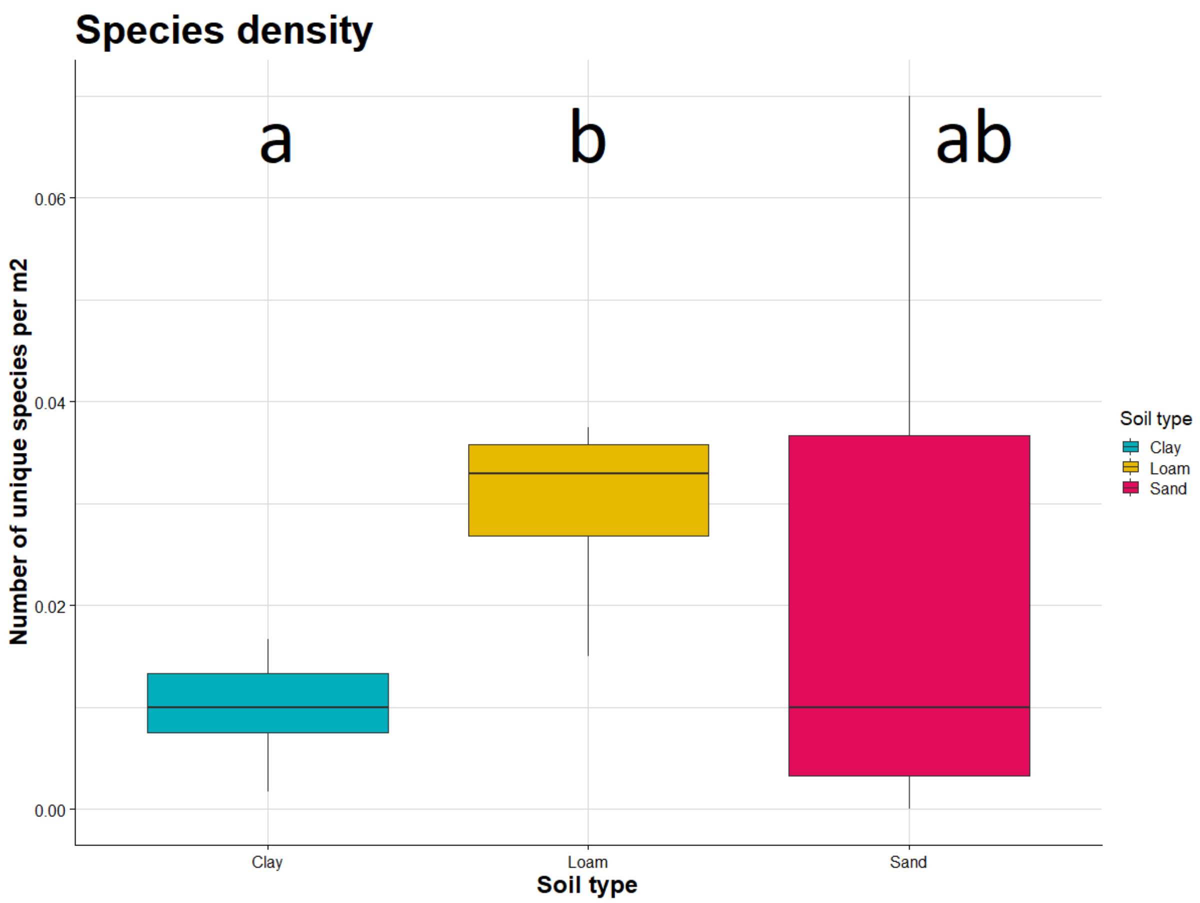


Figure 8. By-soiltype comparison of woody species density in species per m2. N=22. Blue = clay, yellow = loam, Pink = sand. Soil type does not have a significant effect at p=0.068, but this does indicate a 'trend' according to soil type. Clay and sand do not differ significantly (p=0.631), sand and loam do not differ significantly (p= 0.261), and clay and loam differ significantly (p=0.005).

4.4 Plant macronutrients and cation exchange capacity

4.4.1 Plant available soil macronutrients

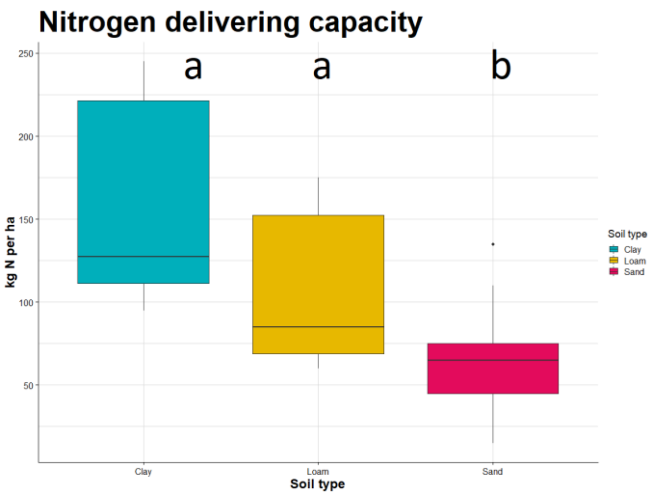
For all participating food forests, soil content of plant available macronutrients (PAM) was analyzed (n=33). For a summary of the results per nutrient, refer to able 1 below.

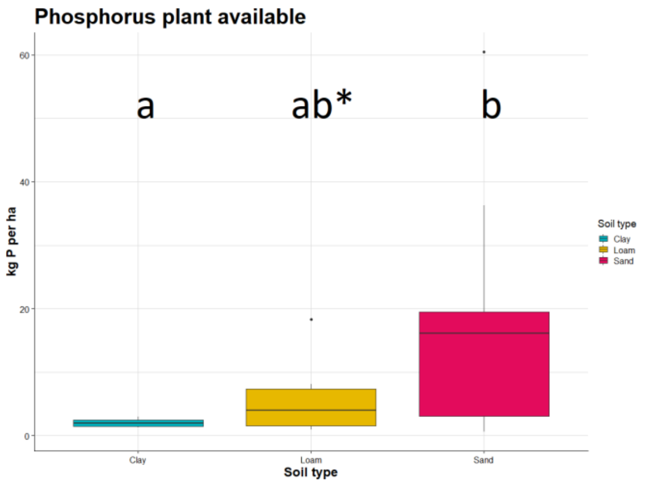
While age did not significantly explain variation in stock of any of the PAM, there was a significant correlation or trend for all PAMs and overall soil type. These findings correspond with the general finding that soil type is a reliable predictor of soil nutrient composition (*Sneha et. al., 2021; Havlin, 2020*).

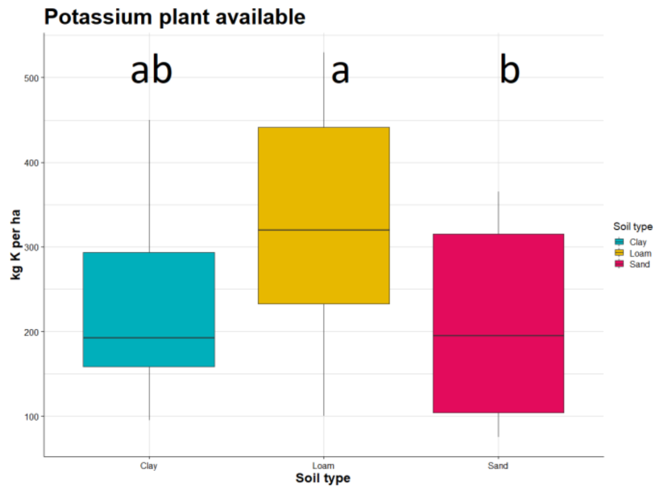
For graphical visualization of nutrients plotted against time, refer to annex figure 4.

Nutrient plant available	Mean value ± sd (kg/ha)	~ Age (years)	~ Soil type overall	~ Sand vs clay	~ Sand vs loam	~ Clay vs loam
N	98.181 ± 57.266	p =0.975 rho = 0.005	p< 0.001	p< 0.001	p=0.033	p=0.103
P	10.45 ± 13.378	p =0.662 rho = -0.08	p= 0.013	p= 0.006	p=0.071	p=0.269
K	244.82 ± 130.74	p =0.287 rho = 0.191	p= 0.211	p=0.6	p=0.091	p=0.227
Mg	319.09 ± 245.60	p =0.187 rho = -0.235	p=0.003	p=0.002	p=0.479	p= 0.036
S	17.66 ± 14.76	p =0.554 rho = -0.109	p= 0.073	p=0.007	p=0.600	p=0.215
Ca	135.24 ± 107.42	p =0.132 rho = 0.267	p= 0.376	p=0.175	p=0.722	p=0.360
Na	40 ± 36.26	p =0.902 rho = -0.023	p= 0.003	p< 0.001	p=0.612	p=0.039

Table 1. Summary of statistics for plant available primary (N,P,K) and secondary (Mg,S,Ca) nutrients, and sodium (Na). Significance levels for statistics are color coded: red = not significant, yellow = 'trend', green = significant. No significant correlation was found between age and any of the nutrients. A negative rho is indicative of a negative relationship between nutrient concentration and age.







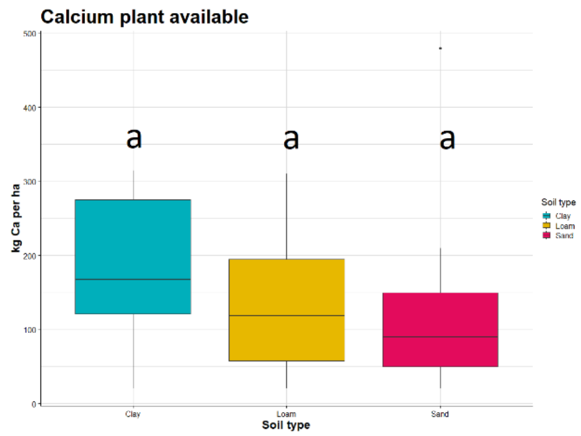


Fig 9 a,b,c,d,e,f,g. By-soil type comparison for plant available primary (N,P,K) and secondary (Mg,S,Ca) nutrients, and sodium (Na). Blue = clay, yellow = loam, Pink = sand. For statistics on macronutrient - soil interactions, please refer to the summary table on the previous page (table x)

No significant relationships were found between any of the analyzed plant available macronutrient concentrations and food forest age. There is a wide spread of concentrations throughout the dataset (*annex fig. 4*). Although it appears that the two oldest food forests have the lowest concentration in all macronutrients but phosphorus, this is to be expected due to the fact that these forests both have sand as their dominant soil type (*see annex fig. 4*).

4.4.2 Soil non plant- available nutrient stock

Alongside plant-available macronutrients, an analysis of the soil stock of plant macronutrients was also performed (n=33). This is the presence of macronutrients that cannot be directly accessed by plants. However, their presence may still be indicative of soil development potential as soil ecosystem properties change.

The soil macronutrients that were analyzed show a strong correlation between elements and the dominant soil type of the forest they were obtained from. All relations between macronutrients and soil type were significant, except for phosphorus ~ soil type. The respective relations give the following P values:

Phosphorus P 0.1178
Nitrogen P 0.00034
Potassium P 0.003829
Calcium P 0.0001593
Magnesium P 0.0004482

Sodium P 0.0004612
Sulphur P 0.005419

In all macronutrients except for phosphorus, clay has the highest concentration of the element, followed by loam and sand (*annex fig. 5*). In phosphorus, the inverse relation is observed with sand having both the highest concentration and largest spread of concentration, followed by loam and then clay (*annex fig. 5*).

No significant relationships were found between any of the analyzed soil stock macronutrient concentrations and food forest age. The spread of nutrient concentrations, and the apparent trend of older forests being lower in nutrients that was observed for plant-available nutrients also holds true for non plant-available soil stock (annex fig. 5). As mentioned above, this ‘trend’ is not significant and most likely explained by the soil type of the two oldest food forests being sand.

4.4.3 Cation Exchange Capacity

For all participating food forests, Cation Exchange Capacity (CEC) of the soil was determined (n=33). The mean CEC was 121.42 ± 105.01 mmol/kg.

A significant difference was found between the cation exchange capacity of food forests of the three dominant soil types. The relationship between CEC and soil type has a P value of 0.0005. Forests on clay have the highest CEC, followed by loam and sand.

Loam has the highest range of CEC values, while sand has the lowest range (*fig 10*).

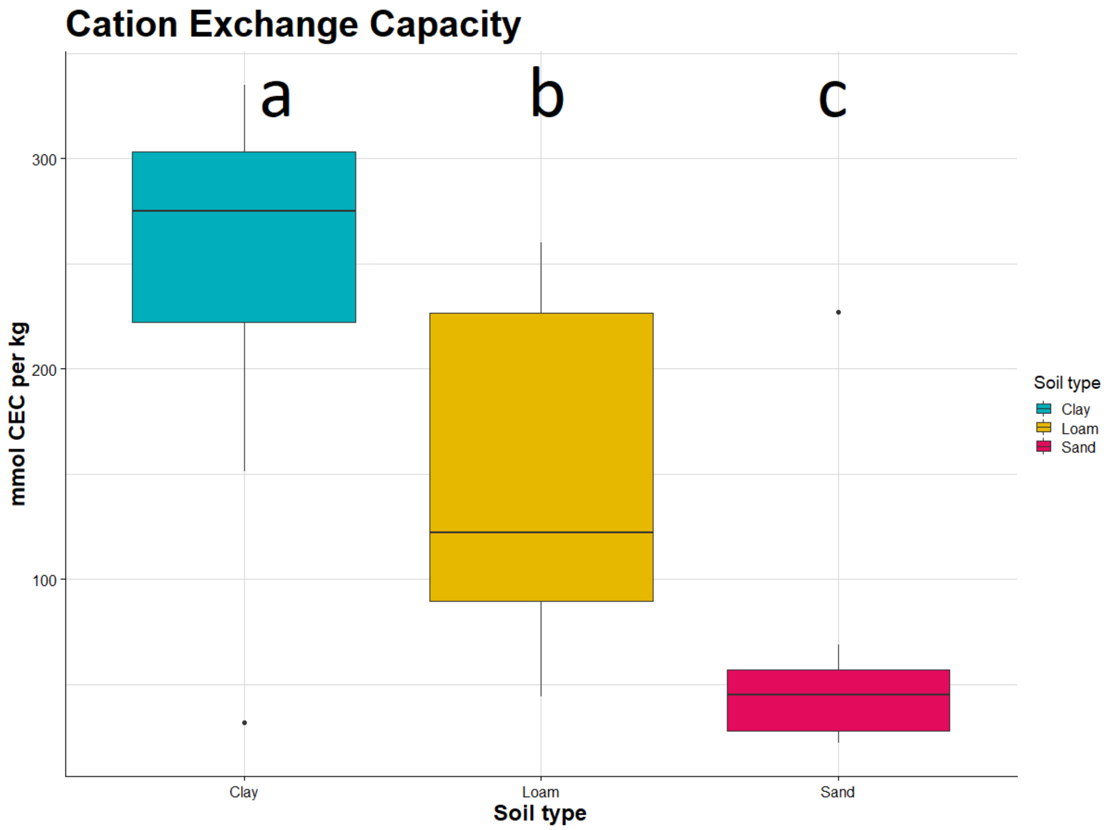


Figure 10. By-soiltype comparison of Cation Exchange Capacity in mmol per kg. N=33. Blue = clay, yellow = loam, Pink = sand. Soil type has a significant effect at p=0.0005. Clay and sand differ significantly (p=0.0013), sand and loam differ significantly (p= 0.0051), and clay and loam differ significantly (p=0.040).

No significant relationship was found between cation exchange capacity and food forest age (p=0.374, rho=0.16). CEC does seem to decrease with age, but this can likely be attributed to the soil type of the oldest two food forests being sand (*annex fig. 6*).

4.5 Earthworms

Earthworms per 20x20x20 cm (8000 cm3) of soil (0-20cm depth) were counted for all 33 participating food forests. Mean average worm count over all plots per forest was 9.09 ± 9.60.

There is no significant relationship between food forest age and earthworm count (p = 0.121 , rho = 0.318). However, the p-value being close to a trend indicates that a stronger effect may be visible when more older food forests will become available for sampling in the future. This possibility is illustrated by a decline in worms over age that is visible graphically (annex fig. 7). However, as mentioned above, there is no significant relationship found in the data, and the sample size for older forests is too small to reliably make predictions.

There is a significant relationship between earthworm count and soil type ($p < 0.05$). Between individual soil types, clay and sand are the only soils that differ significantly ($p = 0.025$). There is a much larger spread in the count of earthworms in clay than in loam and sand (fig 11.).
This large variation in worm count in clay might be explained by the generally poor permeability of clay soils. Worms were counted under different weather conditions, and rainfall in the days leading up to the sampling could lead to a very wet topsoil in some forests. Because only the top 20cm of soil was dug up for worm count, a wet soil could easily influence the behavior of the worms present in the soil- worms tend to migrate upwards during and after periods of rainfall and higher moisture in the soil is generally related with increased earthworm activity (*Edwards & Arancon, 2022*). However, this effect is not controlled for in this study.

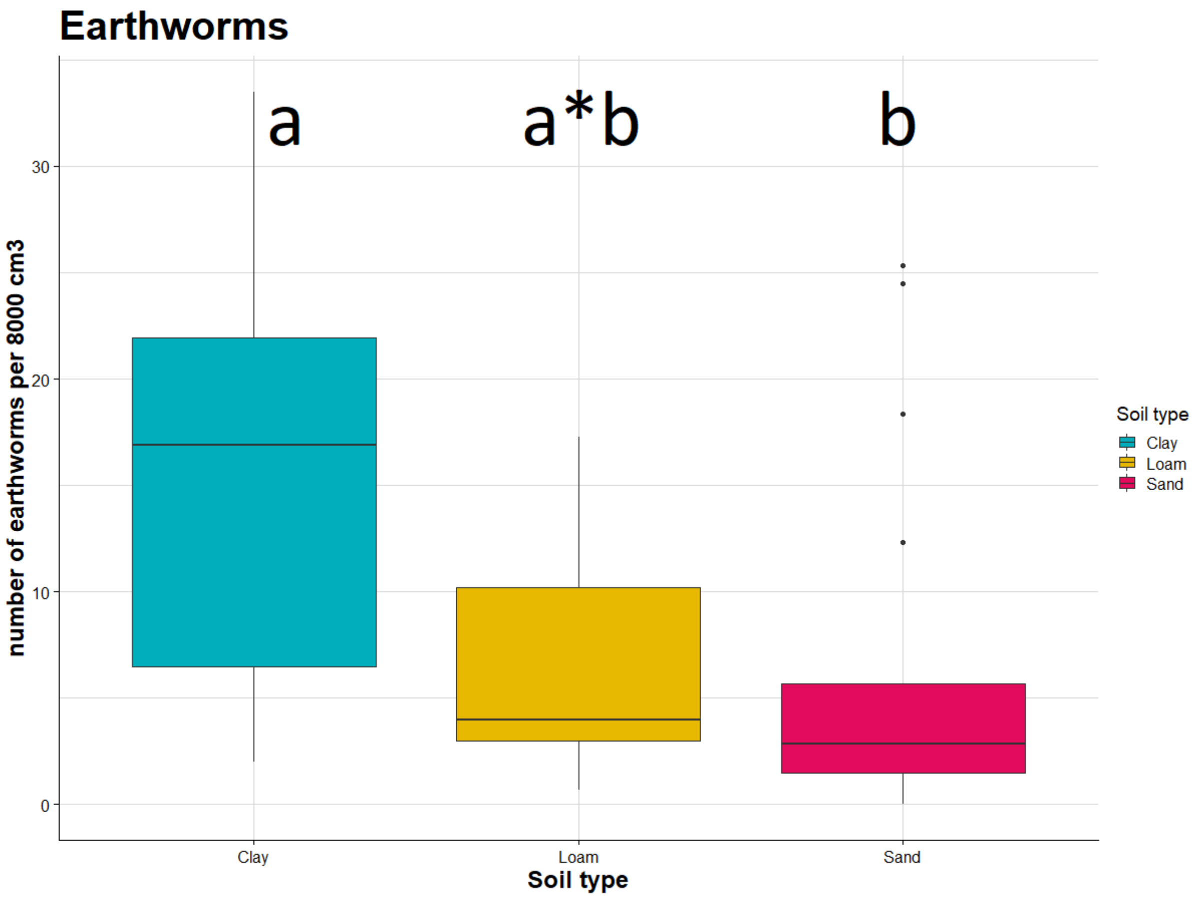


*Figure 11. By-soiltype comparison of number of earthworms per 8000 cm3. N=33. Blue = clay, yellow = loam, Pink = sand. Soil type has a significant effect at p=0.049. Clay and sand differ significantly (p=0.025), sand and loam do not differ significantly (p=0.365), and clay and loam do not differ significantly (p=0.065), although there is a trend between these soil types, indicated by an asterisk * above the boxplot for loam.*

4.6 Multiple Regression Analysis of AGC stock

Using a multiple regression analysis, a generalized linear model (glm) was built that could explain the largest difference in AGC stock with the least, most significant predictor variables.

The glm that best explained the difference in AGC stock had soil type, age, and plant available sodium as predictor variables. The multiple R^2 is 0.834, but due to the multiplicity of variables, using the more conservative adjusted R- squared is advised for estimating true predictability of the model. The adjusted R-squared for the model is 0.7928, meaning that ~ 79 percent of the variation in AGC stock could be explained by the model.

The p-values for the individual variables in the model were:

Soil type (loam) $p = 0.0017$
Soil type (sand) $p = 0.0072$
Age $p < 0.0001$
Sodium plant available $p = 0.001$

For soil type, only loam and sand are given as variables, because of the way in which the glm structure handles categorical variables; a variable of three categories is split up into two independent levels. In this model, this means that since both loam and sand are significant in predicting AGC stock within the model, so is the third soil type, clay.

Age is the most significant factor in predicting AGC stock increase, which is to be expected from the earlier analysis of AGC stock ~ age. This result also means that no matter the state of other predictor variables, food forest AGC stock will increase over time, based on the current findings.

Plant available sodium is also correlated with AGC stock. Sodium was the only plant macronutrient to show a significant relationship to AGC stock within this particular glm. A plot of plant available sodium against AGC stock indicates a negative relationship, where an increase of sodium is associated with a decrease in AGC stock. (*annex graph* 10).

While the best fit glm is adjusted with a lambda transformation to approach normality, it should be noted that the diagnostics plot for this model does show some mild signs of heteroscedasticity (see annex pp. 70-82, diagnostics plots for statistical models). I judged this to be an acceptable deviation from a homogeneity of variance, due to the fact that the line is situated in the middle of the plot and looks overall straight, if slightly tilted. Furthermore, due to the small number of the observations for this model (n=22), single observations strongly influence the trajectory of the scale-location plot.

/ 5. Discussion

5.1 Limitations

Sample sizes

Due to the fact that only 33 food forests were part of the NMVB at the time of this research, the maximum possible sample size for any analysis on food forest level was n=33. While only a bare minimum of three observations is required for most statistical tests, including the entire population if its size does not exceed n=200 is highly recommended (Conroy, 2018). This has been done only for macronutrient, CEC and worm count variables.

Furthermore, the size and difference in size of the 'soil type' subgroups lead to a lower power of the between-group analyses of this predictor variable. However, this effect has been mitigated by working with the entire sample where possible, and only using between-soil type comparisons to tentatively inform data patterns.

Aboveground carbon stock allometric equations

While the VCS allometric equations used in the carbon stock calculation models are widely used for AGC assessment, there is scientific discussion about the applicability of general equations to specific species and growth patterns, such as temperate forests or solitary growth (Henry et. al., 2014 ; Jara et. al., 2010 ; Duncanson et. al., 2015). The VCS does not account for conical growth of tree biomass, while the situation-specific allometric dimensions of models have shown to be crucial in reliably predicting carbon stock (Jara et. al., 2010).

However, due to the variability in growth patterns within Dutch agroforestry, finding a best-fitting correction to the allometric properties of the VCS model would be impossible without surrendering accuracy in some of the measured individuals, unless a specific model would be fitted for each tree species (Henry et. al., 2011). This is impossible in generalized AGC stock assessment across many sites.

Furthermore, application of the VCS has the added benefit of reliable comparison across studies, since it is used in many scientific papers, and has facilitated the comparison between the measured AGC for the NMVB in 2020 and 2022 (Buinink, 2020).

Sandy soil and age outliers

The variation in analyses by soil type and chronosequence may in some part be influenced by the fact that the two oldest food forests in the database are located on sandy soils. As demonstrated, there are strong correlations between most sand and soil macronutrients and earthworms. Therefore, analysis based on age will be influenced by soil class.

Due to the limited size of the dataset and especially due to the low number of older food forests, this effect is unavoidable. However, by statistically analyzing and graphically visualizing soil effects on the database as well as relating variables to soil and age, this effect was mitigated as much as possible.

5.2 The context of global agroforestry research

Agroforestry practices have historically been most conserved in tropical regions, with approximately 78% of agroforestry-designated land situated in tropical regions, and subsequently agroforestry research has been focused primarily on systems in the tropics (*Zomer et. al., 2009 ; Nair et. al., 2022 ; Gordon 2018*). Due to the focus on tropical agroforestry in studies, much is unknown about yield, biodiversity, carbon stock and soil dynamics in temperate food forests (*Oelbermann & Voroney, 2007 ; Gordon 2018 ; Nair et. al., 2009*). However, current research suggests that the aforementioned dynamics in temperate regions differ from findings in the tropics (*Gordon 2010 ; Nair et. al, 2009, Jose et. al., 2004, Ivezíc et. al., 2021*).

Within temperate agroforestry research, the North American continent and parts of Asia are most strongly represented, with less studies focusing on temperate European agroforestry (*Torralba et. al., 2016 ; Mupepele et. al., 2021, Lovell et. al., 2018 ; Chang et. al., 2018*).
While the lack of extensive research on complex interactions in temperate European food forests creates complications for placing this major research project within the context of agroforestry research, it also adds to the relevance of this project.
Studies on the interactions between aboveground and belowground properties of temperate food forests are crucial in ascertaining the benefits of agroforestry, and a greater pool of studied forests in temperate Europe will allow for more powerful analysis of the situation-specific potential of agroforestry (*Torralba et. al., 2016 ; Smith et. al., 2022*).

5.3 Future research

Hedgerow sampling

The results for hedgerow carbon stock show that hedgerows form an interesting component within food forests to separately monitor for carbon stock, due to their high carbon stock in comparison with the food forest body.
Future sampling of developing hedgerows, paired with sampling of their general food forests, will provide insight in the development of the carbon stock ratio for hedgerows and inner part of food forests over time. A comparison against dated reference hedgerows outside of food forests is also recommended in order to predict trends in hedgerow development in lieu of older food forest hedgerows.

Investigating former land use

Investigating the effect of former land use (FLU) in relation to carbon storage can be used to further optimize a carbon prediction model and take into account the diversity of starting situations for agroforestry projects.
FLU has not been included in the final analysis for this research project due to its insignificance in predicting aboveground carbon stock and lack of grouping in the data

based on levels of FLU (see graph: annex fig. 8). However, there is an uneven distribution in age between different land uses (see graph: annex fig. 8), and an analysis which uses the full population of food forests might generate interesting information from FLU.

Sandy soils: soil organisms and carbon dynamics

Due to their physical and chemical qualities, sandy soils were oftentimes outliers in the analyzed data as it pertains to nutrient density, soil organic carbon stock and earthworm count.

It is established that different soil types harbor different soil (macro)fauna, and that sandy soils can harbor an increase in other clades, where earthworms are present less than in other soil types (*P. Hendrix et. al., 1992*). Analyzing different fauna groups for sandy soils can provide a more informed, in-depth perspective on biotic development on sandy food forests, where earthworms have less of a predictive value.

Furthermore, stored soil organic carbon on sandy soils was comparable to clay and loam for young food forests, with a downward trend occurring as sand forests aged (see annex fig. 2). Investigation into the presence of organic carbon related to former land use or grassland degradation is advised to further explore this trend.

Possible effects of sodium on aboveground carbon stock

The generalized linear model analysis conducted in this study did hint to a negative effect of sodium on AGC stock growth. However, due to the bias in sodium prevalence between soil types, and lack of more detailed assessment, it is not possible to accurately extrapolate this finding to the whole body of researched food forests. More specific research into soil sodium content as it relates to AGC stock, where location of the forest, soil type and groundwater salinity are taken into careful account, is recommended to further explore this possible connection,

Use of in-forest plots

One effective way to increase sample size and allow for more complexity in the dataset is to treat in-forest plots as separate individuals within the dataset. This has been done by Kaspar Buinink and Fleur Colen for their 2020 carbon stock assessment for the NMVB, but was not continued in 2022 due to incompatibility problems when aboveground carbon per plot was compared to belowground parameters (*Buinink, 2020*).

However, increased sample size would potentially greatly increase the statistical power of analyses in future research, if homogeneity in variables across sample plots and locations is carefully considered.

Combining research

Within the framework of the NMVB, research is done on food forests that spans a wide variety of themes and disciplines. This major research project has shown that a combination between databases generated through different types of research can provide new perspectives and inform food forest managers on possible management outcomes and challenges. A continuation of an interdisciplinary approach can generate societally relevant results, and also further strengthen the predictive value of research done by the NMVB.

/ 6. Conclusions

Aboveground carbon stock in the measured food forests displayed an exponential-like growth curve after five years of age. The fitting of this curve remains highly uncertain due to the small number of relatively old food forests. If the outlier of 'De Overtuin', which was started in a pre-existing arboretum, is ignored, food forests begin to show meaningful increase in AGC stock after five years of age.
Due to the inclusion of a significantly older food forest, 'Nij Boelens', the initially fitted sigmoid curve from the 2020 carbon stock assessment is no longer appropriate. This suggests that the growth potential in terms of carbon sequestration is larger than previously estimated for food forests.

Most food forests showed an increase in AGC stock compared to 2020, but some forests had similar carbon stocks or decreased in carbon stock compared to two years ago. The outliers in this comparison can be explained by the large effect of a single specimen on a small observed carbon stock, managerial decisions in some forests to cut down trees, and failure to thrive of one food forest. While outliers, these observations paint a more nuanced picture of food forest development; culling and failure to thrive are possible, realistic outcomes of a project.

Including hedgerow carbon stock leads to a much higher estimation of carbon stock per hectare. Hedgerows stored 12 to 6000x more carbon per hectare than the body of food forests. The inclusion of hedgerows in future carbon stock research is recommended, and will lead to a much more realistic calculation of carbon stock per forest if a manager might desire to assess this parameter. Due to the small size of the hedgerow dataset, no conclusions can be drawn beyond the hedgerow's significantly higher carbon stock per hectare in relation to the food forest body.

Soil organic carbon stock was not correlated to food forest age or AGC stock, and showed a weak but statistically significant relationship to soil type. Variation in compaction did not significantly bias SOC stock. It is expected that possible effects of food forest management on SOC stock will require a much longer timescale to become apparent, up to multiple decades based on literature.

Species density was significantly correlated with food forest age. However, age only explained a small percentage of the variety in SD. This is most likely due to the fact that most species are established through human influence, bypassing natural succession processes.

Soil macronutrients and CEC were correlated to soil type, but not to food forest age. This finding underlines the importance of controlling for soil type when analyzing chronosequences, as the oldest two food forests are on sandy soil, which significantly influences perceived trajectory of the dataset for soil macronutrients. Furthermore, soil type is not always taken into account sufficiently in agroforestry studies. This study highlights the strong connections between soil type and levels of belowground variables across a number of categories. If there is a significant effect of agroforestry on soil parameters, which literature does suggest, these processes most likely are much slower than aboveground parameters in a temperate agro-ecology context, and this effect will take more time to be visible from the stock of Dutch food forests.

Earthworm count was correlated to soil type, but not to age. There was especially a difference between worm count on clay versus sand and loam soils. Clay had the highest mean number of worms and widest range. A possible explanation of the wide range in clay is the interaction between weather effects and clay soils. Re-examination of worm count protocols to account for weather effects in more detail is recommended.

A best fit general linear model showed soil type, age and plant-available sodium to be the most significant predictors of AGC stock size out of the available parameters. A model with these three predictor variables explained approximately 80 percent of variation in AGC stock. The relationship of AGC stock with sodium was negative; this finding is supported by literature as sodium toxicity is well established in plant research. While a relationship with soil type might be unreliable due to the age-soil type bias in the (small) food forest dataset, a strong relationship between age and AGC stock is to be expected. The significance of sodium as a predictor of AGC growth remains uncertain due to the biases in the dataset, and lack of adequate information on food forest location and groundwater salinity. Exploring sodium effects on Dutch food forests is an interesting proposal for future research, as the coastal regions of the Netherlands are increasingly exposed to a rise in sodium levels in groundwater.

Bibliography

An R Companion to Applied Regression, Third Edition. Thousand Oaks CA: Sage. URL: https://socialsciences.mcmaster.ca/jfox/Books/Companion/

Anderson E. K. & Zerriffi H. (2012). Seeing the trees for the carbon: agroforestry for development and carbon mitigation. Climatic change 115(3) 741-757.

Asner G. P. Brodrick P. G. Philipson C. Vaughn N. R. Martin R. E. Knapp D. E. ... & Coomes D. A. (2018). Mapped aboveground carbon stocks to advance forest conservation and recovery in Malaysian Borneo. Biological Conservation 217 289-310.

Atangana A. Khasa D. Chang S. & Degrande A. (2014). Major land use issues in the tropics and the history of agroforestry. In Tropical Agroforestry (pp. 23-33). Springer Dordrecht.

Buinink Kaspar. Assessment on the Variation in Carbon Stock of Dutch Food Forests. Utrecht University Major Research Project December 4 (2020).

Burton V. J. & Cameron E. K. (2021). Learning more about earthworms with citizen science. Frontiers for Young Minds.

Cardinael R. Chevallier T. Cambou A. Beral C. Barthès B. G. Dupraz C. ... & Chenu C. (2017). Increased soil organic carbon stocks under agroforestry: A survey of six different sites in France. Agriculture Ecosystems & Environment 236 243-255.

Cardinael R. Mao Z. Chenu C. & Hinsinger P. (2020). Belowground functioning of agroforestry systems: recent advances and perspectives. Plant and Soil 453(1) 1-13.

Carswell F. E. Burrows L. E. & Mason N. W. H. (2009). Above-ground carbon sequestration by early-successional woody vegetation: a preliminary analysis. Science for Conservation (297).

Chang S. X. Wang W. Zhu Z. Wu Y. & Peng X. (2018). Temperate agroforestry in China. Temperate agroforestry systems 173-194.

Conroy Ronán. (2018). The RCSI Sample size handbook. 10.13140/RG.2.2.30497.51043.

De Beenhouwer M. Geeraert L. Mertens J. Van Geel M. Aerts R. Vanderhaegen K. & Honnay O. (2016). Biodiversity and carbon storage co-benefits of coffee agroforestry across a gradient of increasing management intensity in the SW Ethiopian highlands. Agriculture Ecosystems & Environment 222 193-199.

Diana Feliciano Alicia Ledo Jon Hillier Dali Rani Nayak Which agroforestry options give the greatest soil and above ground carbon benefits in different world regions? Agriculture Ecosystems & Environment Volume 254 2018 Pages 117-129 ISSN 0167-8809 https://doi.org/10.1016/j.agee.2017.11.032.

Duncanson L. Rourke O. & Dubayah R. Small Sample Sizes Yield Biased Allometric Equations in Temperate Forests. Sci Rep 5 17153 (2015). https://doi.org/10.1038/srep17153

Dupraz C. Lawson G. J. Lamersdorf N. Papanastasis V. P. Rosati A. & Ruiz-Mirazo J. (2018). Temperate agroforestry: the European way. Temperate agroforestry systems 98-152.

E. Lapied J. Nahmani G.X. Rousseau Influence of texture and amendments on soil properties and earthworm communities Applied Soil Ecology Volume 43 Issues 2–3 2009 Pages 241-249 ISSN 0929-1393 https://doi.org/10.1016/j.apsoil.2009.08.004. Lapied E. Nahmani J. & Rousseau G. X. (2009). Influence of texture and amendments on soil properties and earthworm communities. Applied Soil Ecology 43(2-3) 241-249.

Edmonds M. (1999). Ancestral Geographies of the Neolithic: Landscapes Monuments and Memory (1st ed.). Routledge. https://doi.org/10.4324/9780203020197

Eurofins Agro. Toelichting Bemestingswijzer. 2022. https://www.eurofins-agro.com/nl-nl/bemestingswijzer

Feliciano D. Ledo A. Hillier J. & Nayak D. R. (2018). Which agroforestry options give the greatest soil and above ground carbon benefits in different world regions?. Agriculture ecosystems & environment 254 117-129.

Fifanou V.G. Ousmane C. Gauthier B. et al. Traditional agroforestry systems and biodiversity conservation in Benin (West Africa). Agroforest Syst 82 1–13 (2011). https://doi.org/10.1007/s10457-011-9377-4

Fischer C. Roscher C. Jensen B. Eisenhauer N. Baade J. Attinger S. ... & Hildebrandt A. (2014). How do earthworms soil texture and plant composition affect infiltration along an experimental plant diversity gradient in grassland?. PloS one 9(6) e98987.

Food and agriculture organization of the Unite Nations. Agroforestry. last updated: Friday October 23 2015. https://www.fao.org/forestry/agroforestry/80338/en/

Food and Agriculture Organization of the United Nations. Agroforestry.

Fründ HC. Graefe U. Tischer S. (2011). Earthworms as Bioindicators of Soil Quality. In: Karaca A. (eds) Biology of Earthworms. Soil Biology vol 24. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-14636-7_16

Gatzweiler F. (2003). Patterns of institutional change for sustainability in Central and Eastern European agriculture.

Geoff H. Baker Wendy A. Whitby Soil pH preferences and the influences of soil type and temperature on the survival and growth of Aporrectodea longa (Lumbricidae): The 7th international symposium on earthworm ecology · Cardiff · Wales · 2002 Pedobiologia Volume 47 Issues 5–6 2003 Pages 745-753 ISSN 0031-4056 https://doi.org/10.1078/0031-4056-00254. (https://www.sciencedirect.com/science/article/pii/S0031405604702632)

Gingrich S. Erb K. H. Krausmann F. Gaube V. & Haberl H. (2007). Long-term dynamics of terrestrial carbon stocks in Austria: a comprehensive assessment of the time period from 1830 to 2000. Regional Environmental Change 7(1) 37-47.

Golicz K Ghazaryan G Niether W Wartenberg AC Breuer L Gattinger A Jacobs SR Kleinebecker T Weckenbrock P Große-Stoltenberg A. The Role of Small Woody Landscape Features and Agroforestry Systems for National Carbon Budgeting in Germany. Land. 2021; 10(10):1028. https://doi.org/10.3390/land10101028

Gordon A. M. Newman S. M. & Coleman B. (Eds.). (2018). Temperate agroforestry systems. CABI.

Granata M. U. Gratani L. Bracco F. Sartori F. & Catoni R. (2016). Carbon stock estimation in an unmanaged old-growth forest: a case study from a broad-leaf deciduous forest in the Northwest of Italy. International Forestry Review 18(4) 444-451.

Green Deal Voedselbossen (Green Deal Food Forests) (2019). Retrieved 2022 from https://www.greandeelvoedselbossen.nl/green-deal-voedselbossen/.

Gregory P. Asner Philip G. Brodrick Christopher Philipson Nicolas R. Vaughn Roberta E. Martin David E. Knapp Joseph Heckler Luke J. Evans Tommaso Jucker Benoit Goossens Danica J. Stark Glen Reynolds Robert Ong Nathan Renneboog Fred Kugan David A. Coomes Mapped aboveground carbon stocks to advance forest conservation and recovery in Malaysian Borneo Biological Conservation Volume 217 2018 Pages 289-310 ISSN 0006-3207 https://doi.org/10.1016/j.biocon.2017.10.020.

Guo L. B. & Gifford R. M. (2002). Soil carbon stocks and land use change: a meta analysis. Global change biology 8(4) 345-360.

H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York 2016.

Havlin J. L. (2020). Soil: Fertility and nutrient management. In Landscape and land capacity (pp. 251-265). CRC Press.

Hendrix P. F. Mueller B. R. Bruce R. R. Langdale G. W. & Parmelee R. W. (1992). Abundance and distribution of earthworms in relation to landscape factors on the Georgia Piedmont USA. Soil Biology and Biochemistry 24(12) 1357-1361.

Henry M. Besnard A. Asante W. A. Eshun J. Adu-Bredu S. Valentini R. ... & Saint-André L. (2010). Wood density phytomass variations within and among trees and allometric equations in a tropical rainforest of Africa. Forest Ecology and Management 260(8) 1375-1388.

Herzog F. (1998). Agroforestry in temperate Europe: history present importance and future development. Keulen H van Lantinga EA and van Laar HH (eds) Mixed Farming Systems in Europe 47-52.

Herzog F. (1998). Streuobst: a traditional agroforestry system as a model for agroforestry development in temperate Europe. Agroforestry systems 42(1) 61-80.

Hudiburg T. Law B. Turner D. P. Campbell J. Donato D. & Duane M. (2009). Carbon dynamics of Oregon and Northern California forests and potential land-based carbon storage. Ecological applications 19(1) 163-180.

Iannone B. V. Umek L. G. Wise D. H. & Heneghan L. (2012). A simple safe and effective sampling technique for investigating earthworm communities in woodland soils: implications for citizen science. Natural Areas Journal 32(3) 283-292.

Islam M. Dey A. & Rahman M. Effect of Tree Diversity on Soil Organic Carbon Content in the Homegarden Agroforestry System of North-Eastern Bangladesh. Small-scale Forestry 14 91–101 (2015). https://doi.org/10.1007/s11842-014-9275-5

Ivezić Vladimir Yu Yang Werf Wopke van der. Crop Yields in European Agroforestry Systems: A Meta-Analysis. Frontiers in Sustainable Food Systems VOLUME 5. 2021. 10.3389/fsufs.2021.606631. ISSN 2571-581X

John Fox and Sanford Weisberg (2019). An {R} Companion to Applied Regression Third Edition.

Jones I. L. DeWalt S. J. Lopez O. R. Bunnefeld L. Pattison Z. & Dent D. H. (2019). Above-and belowground carbon stocks are decoupled in secondary tropical forests and are positively related to forest age and soil nutrients respectively. Science of The Total Environment 697 133987.

Jose S. Gillespie A. & Pallardy S. Interspecific interactions in temperate agroforestry. Agroforestry Systems 61 237–255 (2004). https://doi.org/10.1023/B:AGFO.0000029002.85273.9b

Keijzers G. (2000). The evolution of Dutch environmental policy: the changing ecological arena from 1970–2000 and beyond. Journal of Cleaner Production 8(3) 179-200.

King K. F. S. (1987). The history of agroforestry. Agroforestry 1.

Korevaar H. (1992). The nitrogen balance on intensive Dutch dairy farms: a review. Livestock Production Science 31(1-2) 17-27.

Kronzucker H. J. Coskun D. Schulze L. M. Wong J. R. & Britto D. T. (2013). Sodium as nutrient and toxicant. Plant and soil 369(1) 1-23.

Lavelle P. 1988. Earthworms and the soil system. Biol. Fertil. Soil 6 237-251

Lejon D.P.H. Chaussod R. Ranger J. et al. Microbial Community Structure and Density Under Different Tree Species in an Acid Forest Soil (Morvan France). Microb Ecol 50 614–625 (2005). https://doi.org/10.1007/s00248-005-5130-8

Levy P. E. Hale S. E. & Nicoll B. C. (2004). Biomass expansion factors and root: shoot ratios for coniferous tree species in Great Britain. Forestry 77(5) 421-430.

Lomolino M.V. (2001) Elevation gradients of species-density: historical and prospective views. Global Ecology and Biogeography 10: 3-13. https://doi.org/10.1046/j.1466-822x.2001.00229.x

Lovell S.T. Dupraz C. Gold M. et al. Temperate agroforestry research: considering multifunctional woody polycultures and the design of long-term field trials. Agroforest Syst 92 1397–1415 (2018). https://doi.org/10.1007/s10457-017-0087-4

Lowe C. N. & Butt K. R. (2002). Influence of organic matter on earthworm production and behaviour: a laboratory-based approach with applications for soil restoration. European Journal of Soil Biology 38(2) 173-176.

Luke J. Schafer Marin Lysák Christian B. Henriksen Tree layer carbon stock quantification in a temperate food forest: A peri-urban polyculture case study Urban Forestry & Urban Greening Volume 45 2019 126466 ISSN 1618-8667 https://doi.org/10.1016/j.ufug.2019.126466.

M. Henry A. Besnard W.A. Asante J. Eshun S. Adu-Bredu R. Valentini M. Bernoux L. Saint-André Wood density phytomass variations within and among trees and allometric equations in a tropical rainforest of Africa Forest Ecology and Management Volume 260 Issue 8 2010 Pages 1375-1388 ISSN 0378-1127 https://doi.org/10.1016/j.foreco.2010.07.040.

Maathuis F. J. (2009). Physiological functions of mineral macronutrients. Current opinion in plant biology 12(3) 250-258.

Maathuis F. J. (2014). Sodium in plants: perception signalling and regulation of sodium fluxes. Journal of Experimental Botany 65(3) 849-858.

Manaye A. Tesfamariam B. Tesfaye M. Worku A. & Gufi Y. (2021). Tree diversity and carbon stocks in agroforestry systems in northern Ethiopia. Carbon Balance and Management 16(1) 1-10.

Maren Oelbermann R. Paul Voroney Carbon and nitrogen in a temperate agroforestry system: Using stable isotopes as a tool to understand soil dynamics Ecological Engineering Volume 29 Issue 4 2007 Pages 342-349 ISSN 0925-8574 https://doi.org/10.1016/j.ecoleng.2006.09.014. Oelbermann M. & Voroney R. P. (2007). Carbon and nitrogen in a temperate agroforestry system: using stable isotopes as a tool to understand soil dynamics. ecological engineering 29(4) 342-349.

Mario Torralba Nora Fagerholm Paul J. Burgess Gerardo Moreno Tobias Plieninger. Do European agroforestry systems enhance biodiversity and ecosystem services? A meta-analysis Agriculture Ecosystems & Environment Volume 230 2016 Pages 150-161 ISSN 0167-8809 https://doi.org/10.1016/j.agee.2016.06.002.

Mäser P. Gierth M. & Schroeder J. I. (2002). Molecular mechanisms of potassium and sodium uptake in plants. In Progress in plant nutrition: plenary lectures of the XIV international plant nutrition colloquium (pp. 43-54). Springer Dordrecht.

Matieu Henry Nicolas Picard Carlo Trotta Raphaël Manlay Riccardo Valentini et al.. Estimating Tree Biomass of Sub-Saharan African Forests: a Review of Available Allometric Equations. Silva Fennica Suomen Metsätieteellinen Seura ry 2011 45 (3) pp.477 - 569. ⟨hal-02651041⟩

Montagnini F. & Nair P. K. R. (2004). Carbon sequestration: an underexploited environmental benefit of agroforestry systems. In New vistas in agroforestry (pp. 281-295). Springer Dordrecht.

Mosa K. A. Ali M. A. Ramamoorthy K. & Ismail A. (2022). Exploring the relationship between plant secondary metabolites and macronutrient homeostasis. In Plant Nutrition and Food Security in the Era of Climate Change (pp. 119-146). Academic Press.

Mosquera-Losada M. R. Santiago Freijanes J. J. Pisanelli A. Rois M. Smith J. den Herder M. ... & Burgess P. J. (2016). Extent and success of current policy measures to promote agroforestry across Europe. AGFORWARD European Project Policy Report: Bruxelles Belgium.

Mupepele AC. Keller M. & Dormann C.F. European agroforestry has no unequivocal effect on biodiversity: a time-cumulative meta-analysis. BMC Ecol Evo 21 193 (2021). https://doi.org/10.1186/s12862-021-01911-9

Murthy I. K. Gupta M. Tomar S. Munsi M. Tiwari R. Hegde G. T. & Ravindranath N. H. (2013). Carbon sequestration potential of agroforestry systems in India. J Earth Sci Climate Change 4(1) 1-7.

Muys B. & Lust N. (1992). Inventory of the earthworm communities and the state of litter decomposition in the forests of Flanders Belgium and its implications for forest management. Soil Biology and Biochemistry 24(12) 1677-1681.

Nair P. R. Nair V. D. Kumar B. M. & Showalter J. M. (2010). Carbon sequestration in agroforestry systems. Advances in agronomy 108 237-307.

Nair P.K.R. Kumar B.M. Nair V.D. (2021). Global Distribution of Agroforestry Systems. In: An Introduction to Agroforestry. Springer Cham. https://doi.org/10.1007/978-3-030-75358-0_4

Nath A. J. Lal R. & Das A. K. (2015). Managing woody bamboos for carbon farming and carbon trading. Global Ecology and Conservation 3 654-663.

Nationaal Monitoringsprogramma Voedselbossen (National Monitoring Program Food Forests) 2022. Retrieved 2022. https://www.monitoringvoedselbossen.nl/

Needelman B.A. Emmer I.M. Emmett-Mattox S. et al. The Science and Policy of the Verified Carbon Standard Methodology for Tidal Wetland and Seagrass Restoration. Estuaries and Coasts 41 2159–2171 (2018). https://doi.org/10.1007/s12237-018-0429-0

Newman S. M. & Gordon A. M. (2018). Temperate agroforestry: key elements current limits and opportunities for the future. In Temperate agroforestry systems (pp. 274-298). Wallingford UK: CAB International.

P.F. Hendrix B.R. Mueller R.R. Bruce G.W. Langdale R.W. Parmelee

P.K. Ramachandran Nair Vimala D. Nair B. Mohan Kumar Julia M. Showalter Chapter Five - Carbon Sequestration in Agroforestry Systems Editor(s): Donald L. Sparks Advances in Agronomy Academic Press Volume 108 2010 Pages 237-307 ISSN 0065-2113 ISBN 9780123810311 https://doi.org/10.1016/S0065-2113(10)08005-3.

Petersson H. Holm S. Ståhl G. Alger D. Fridman J. Lehtonen A. ... & Mäkipää R. (2012). Individual tree biomass equations or biomass expansion factors for assessment of carbon stock changes in living biomass–A comparative study. Forest Ecology and Management 270 78-84.

Pretzsch H. & Biber P. (2016). Tree species mixing can increase maximum stand density. Canadian Journal of Forest Research 46(10) 1179-1193.

Pretzsch H. Schütze G. Effect of tree species mixing on the size structure density and yield of forest stands. Eur J Forest Res 135 1–22 (2016). https://doi.org/10.1007/s10342-015-0913-z

R Core Team (2019). A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Ramachandran Nair P. K. Mohan Kumar B. & Nair V. D. (2009). Agroforestry as a strategy for carbon sequestration. Journal of plant nutrition and soil science 172(1) 10-23.

Ramos H. M. N. Vasconcelos S. S. Kato O. R. & Castellani D. C. (2018). Above-and belowground carbon stocks of two organic agroforestry-based oil palm production systems in eastern Amazonia. Agroforestry Systems 92(2) 221-237.

Rao M.R. Nair P.K.R. & Ong C.K. Biophysical interactions in tropical agroforestry systems. Agroforestry Systems 38 3–50 (1997). https://doi.org/10.1023/A:1005971525590

Risch A. C. Jurgensen M. F. Page-Dumroese D. S. Wildi O. & Schütz M. (2008). Long-term development of above-and below-ground carbon stocks following land-use change in subalpine ecosystems of the Swiss National Park. Canadian Journal of Forest Research 38(6) 1590-1602.

Römbke J. Jänsch S. & Didden W. 2005. The use of earthworms in ecological soil classification and assessment concepts. Ecotoxocological Environ. Saf. 62 249-265.

Römbke J. Schmidt P. & Höfer H. (2009). The earthworm fauna of regenerating forests and anthropogenic habitats in the coastal region of Paraná. Pesquisa Agropecuaria Brasileira 44 1040-1049.

Roy O. Meena R. S. Kumar S. Jhariya M. K. & Pradhan G. (2022). Assessment of land use systems for CO2 sequestration carbon credit potential and income security in Vindhyan region India. Land Degradation & Development 33(4) 670-682.

RStudio Team (2019). RStudio: Integrated Development for R. RStudio PBC Boston MA URL http://www.rstudio.com/.

Saha S.K. Nair P.K.R. Nair V.D. et al. Soil carbon stock in relation to plant diversity of homegardens in Kerala India. Agroforest Syst 76 53–65 (2009). https://doi.org/10.1007/s10457-009-9228-8

Saha, Uttam K. Cation Exchange Capacity and Base Saturation. University of Georgia Extension Mar 28 2017.
https://extension.uga.edu/publications/detail.html?number=c1040#:~:text=Cation%20exchange%20capacity%20(CEC)%20issoil%20solution%20for%20plant%20uptake.

Santiago-Freijanes J. J. Pisanelli A. Rois-Díaz M. Aldrey-Vázquez J. A. Rigueiro-Rodríguez A. Pantera A. ... & Mosquera-Losada M. R. (2018). Agroforestry development in Europe: Policy issues. Land use policy 76 144-156.

Sinfield J. V. Fagerman D. & Colic O. (2010). Evaluation of sensing technologies for on-the-go detection of macro-nutrients in cultivated soils. Computers and Electronics in Agriculture 70(1) 1-18.

Skog K.E. & Nicholson G.A. (1998). Carbon cycling through wood products : The role of wood and paper products in carbon sequestration. Forest Products Journal 48 75-83.

Sneha G. R. Swarnalakshmi K. Sharma M. Reddy K. Bhoumik A. Suman A. & Kannepalli A. (2021). Soil type influence nutrient availability microbial metabolic diversity eubacterial and diazotroph abundance in chickpea rhizosphere. World Journal of Microbiology and Biotechnology 37(10) 1-15.

Stokstad E. (2019). Nitrogen crisis threatens Dutch environment—and economy.

Strand E. K. Vierling L. A. Smith A. M. S. and Bunting S. C. (2008) Net changes in aboveground woody carbon stock in western juniper woodlands 1946–1998 J. Geophys. Res. 113 G01013 doi:10.1029/2007JG000544.

Subbarao G. V. Ito O. Berry W. L. & Wheeler R. M. (2003). Sodium—a functional plant nutrient. Critical Reviews in Plant Sciences 22(5) 391-416.

Subhrendu Pattanayak D. Evan Mercer Valuing soil conservation benefits of agroforestry: contour hedgerows in the Eastern Visayas Philippines Agricultural Economics Volume 18 Issue 1 1998 Pages 31-46 ISSN 0169-5150

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 & environment 230 150-161.

Tripathi Durgesh Kumar et al. "Role of macronutrients in plant growth and acclimation: recent advances and future prospective." Improvement of crops in the era of climatic changes (2014): 197-216.

Tripathi G. & Bhardwaj P. (2004). Earthworm diversity and habitat preferences in arid regions of Rajasthan. Zoo's Print Journal 19(7) 1515-1519.

Van Vinh T. Marchand C. Linh T. V. K. Vinh D. D. & Allenbach M. (2019). Allometric models to estimate above-ground biomass and carbon stocks in Rhizophora apiculata tropical managed mangrove forests (Southern Viet Nam). Forest Ecology and Management 434 131-141.

Venables W. N. & Ripley B. D. (2002) Modern Applied Statistics with S. Fourth Edition. Springer, New York. ISBN 0-387-95457-0

Verra. (n.d.). Verified Carbon Standard. Retrieved November 5 2020 from https://verra.org/methodologies/.

Von Avenarius A Devaraja TS Kiesel R. An Empirical Comparison of Carbon Credit Projects under the Clean Development Mechanism and Verified Carbon Standard. Climate. 2018; 6(2):49. https://doi.org/10.3390/cli6020049

Wendel B. (2021 August 19). Carbon sequestration in young temperate food forests: A case study analysis on a chronosequence of the transition from grassland to food forests. ripository.tudelft.nl. Retrieved from https://repository.tudelft.nl/islandora/object/uuid:c0e3630d-4eee-472a-9938-e77e85155f16?collection=education

Wills C. Condit R. Foster R. B. & Hubbell S. P. (1997). Strong density-and diversity-related effects help to maintain tree species diversity in a neotropical forest. Proceedings of the National Academy of Sciences 94(4) 1252-1257.

World Agroforestry Database Wood Density Index. Accessed January - November 2022. http://db.worldagroforestry.org/wd

Yeo A. R. & Flowers T. J. (1983). Varietal differences in the toxicity of sodium ions in rice leaves. Physiologia Plantarum 59(2) 189-195.

Yvan C. Stéphane S. Stéphane C. Pierre B. Guy R. & Hubert B. (2012). Role of earthworms in regenerating soil structure after compaction in reduced tillage systems. Soil Biology and Biochemistry 55 93-103.

Zirbes L. Thonart P. & Haubruge E. (2012). Microsale interactions between earthworms and microorganisms a review. Biotechnologie Agronomie Société et Environnement 16(1).

Zomer R. J. ; Trabucco A. ; Coe R. ; Place F. Trees on farm: analysis of global extent and geographical patterns of agroforestry. ICRAF Working Paper - World Agroforestry Centre 2009 No.89 pp.63 pp. ref.30

[Original source alphabetization: https://studycrumb.com/alphabetizer]

Annex: list of participating food forests and data collected

Food forest name	Soil type	Age	AGC	AGC HR	SOC	AGC 2020
De Overtuin	Loam	3				
Houtrak	Clay	5				
Amsterdam	Loam	6				
Eemvallei Zuid	Clay	4				
Droevendaal	Clay	3				
Het Voedselrijk	Sand	3				
Thuishaven	Sand	2				
Den Food Bosch / Volmeer	Sand	5				
Schijndel Boschweg	Sand	3				
Schijndel Hardekamp	Loam	3				
Ketelbroek	Loam	13				
Groengenoten	Sand	3				
Sualmana	Sand	23				
Vlaardingen	Loam	7				
Benthuizen	Clay	4				
De Stomp	Loam	3				
Kreilerwoud	Loam	5				
Roggebotstaete	Loam	6				
d'Ekkers	Sand	2				
Breedenbroek	Sand	2				
Lekker landgoed	Clay	5				
Schevichoven	Sand	1				
Het Loonse Bos	Sand	2				
Heische Hoeve	Sand	2				
De Pullenhap	Sand	2				
Ruurhoeve	Sand	1				
Woensdrecht	Sand	2				
Vierhoeven	Sand	1				
Nij Boelens	Sand	28				
Binnenbos	Clay	1				
De Terp	Clay	2				
Leukerbos	Sand	2				

Laakoever	Clay	0				

Annex table 1. List of participating food forests of the NMVB, with index of variables collected per food forest. AGC= aboveground carbon stock, AGC HR = aboveground carbon stock of hedgerows, SOC = soil organic carbon, AGC 2020 = aboveground carbon stock collected in 2020. Note that some forests had their AGC stock assessed in 2020, but were not included in the data analysis because they did not have their AGC stock assessed in 2022, and therefore no comparison could be made. Also note that for the other variables collected for this major research project, all 33 food forests were sampled. Therefore, their mention is omitted from this table. This concerns the following variables: worm count, compaction, soil macronutrient stock plant-available and non plant-available, CEC.

Annex: protocols

GIS sampling protocol for NMVB

The sample point protocol with which all of the participating forests were fitted is as follows:

1. In the free georeferencing software QGIS, the exact parameters of the food forest are located on satellite image using data from the Dutch Kadaster. If possible, a map of the food forest is used as an overlay so that its exact location on the satellite map can be obtained. From this information, the borders of the food forest can be drawn.

2. After border selection, the whole surface of the food forest is fitted with a grid which fits within the borders of the forest. The grid consists of 10x10 meter squares. If a square partially falls outside of the borders of the food forest, it is removed.

3. When the grid is completed, a set of sample points will be selected. The rules for the amount of points that are to be selected are as follows:

'Worm' points: one worm point for every 1/3 ha of land, with a minimum of three points per forest, and a maximum of six points per forest.

Soil sample points: one point for every 0,1 ha of land, with a minimum of fifteen points per forest, and a maximum of thirty points per forest.

When the amount of points for both subsets of sampling is determined, the research tool available on QGIS is used to randomly select the desired number of squares from the grid. The center point of the selected squares will be used as the sample points.

4. The selected points from both subsets are checked for workability: if a selected point falls right upon a path or a structural building, it is moved one grid square to the next eligible sampling location based on the following order: West, South, East, North.

5. When appropriately selected, the grid and sample points are exported as .kml files so that they can be imported in Google Maps, using the 'My Maps' function.

Aboveground carbon sample squares

The selection of sampling locations for the aboveground carbon storage was done in a very similar fashion to that of the standardized sampling points. Because the aboveground carbon measurements were done in plots of 10x10 meters, the grid used for point selection can also be seamlessly applied to square selection for aboveground

carbon measurement.
Furthermore, where possible the squares selected are ones that already have a 'worm point' as the center of the square, so that locations are easier to manage and revisit across research.

Protocol for sample collection for Eurofins analysis (Dutch)

Benodigde materialen:

Emmer, gutsboor, lineaal, duimpje/schraper (of ander lang en dun puntvormig object), markeerstift en 2 doorzichtige diepvries zakken

Aantal meetpunten

15 per hectare, min 15. max 30. Random geselecteerd in 10mx10m grid. Alle gele/oranje punten op de kaart (de blauwe punten zijn tevens gele punten)

Stappenplan

1. Steek bij elk geel meetpunt een monster met de gutsboor tot minimaal 25 cm diep (nameten met lineaal)

2. Draai de gutsboor op het diepste punt een halve slag zodat de grond mee omhoog komt

3. Markeer de bovenste 25cm met behulp van de lineaal

4. Schraap met het duimpje/de schraper (of een ander puntvormig object) het eventuele teveel grond onder de 25cm markering uit de gutsboor weg

5. Schraap de bovenste 25cm grond vanaf de markering in de emmer en vind het volgende punt

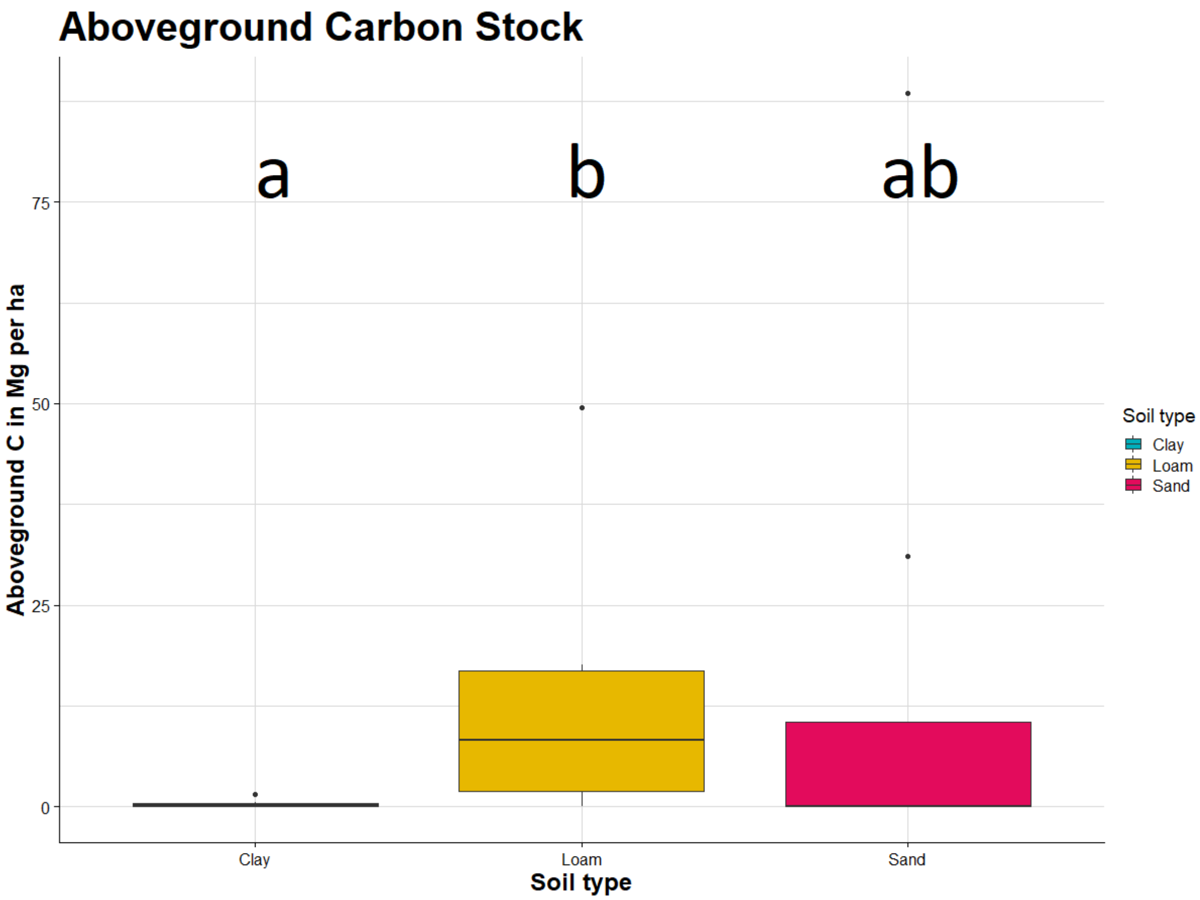
6. Verwijder na de laatste monstername alle groene plantenresten die in de emmer terecht zijn gekomen met de hand

7. Meng alle monsters goed in de emmer

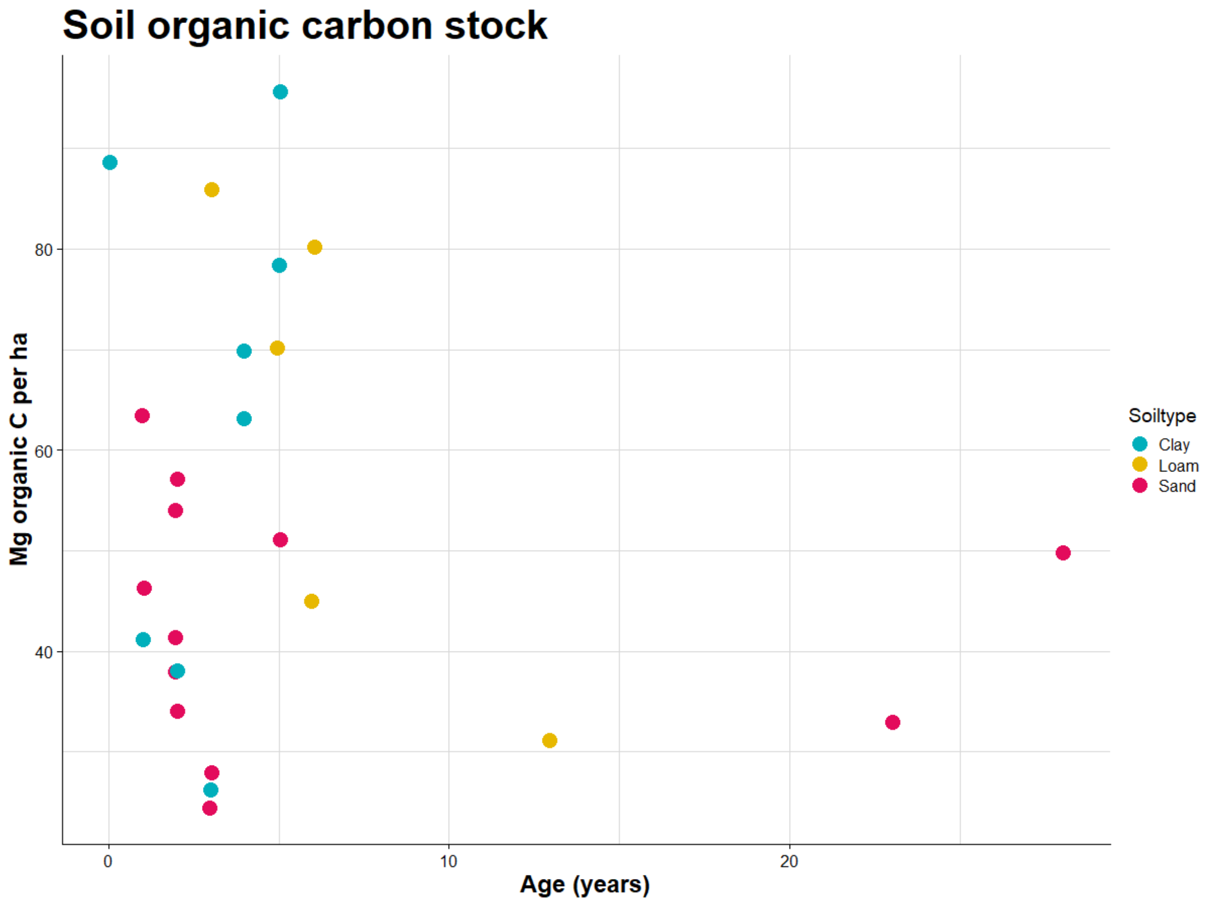
8. Doe het 0.5kg van het mengsel in een zak en noteer met de markeerstift locatie, ID ,plaats , datum en bestemming (Eurofins lab)

9. Doe het 0.5kg van het mengsel in de andere zak en noteer met de markeerstift locatie, ID ,plaats , datum en bestemming (NIOO/WUR lab)

Annex: graphics of the results



Annex Figure 1. By-soiltype comparison of aboveground carbon stock in Mg per ha. N=22. Blue = clay, yellow = loam, Pink = sand. Soil type does not have a significant effect at p=0.125. Clay and sand do not differ significantly (p=0.6434), sand and loam do not differ significantly (p=0.3662), and clay and loam differ significantly (p=0.01516)

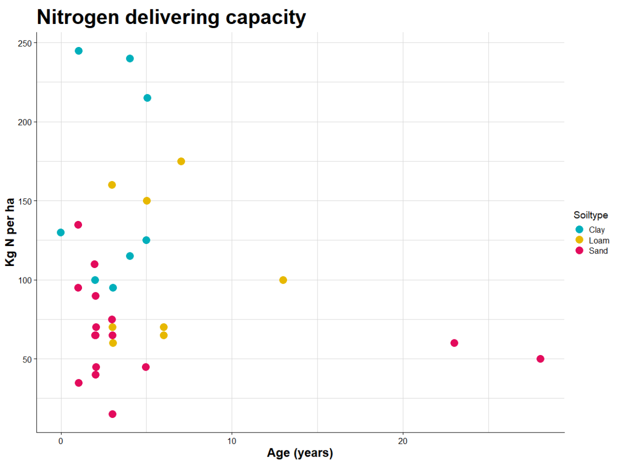


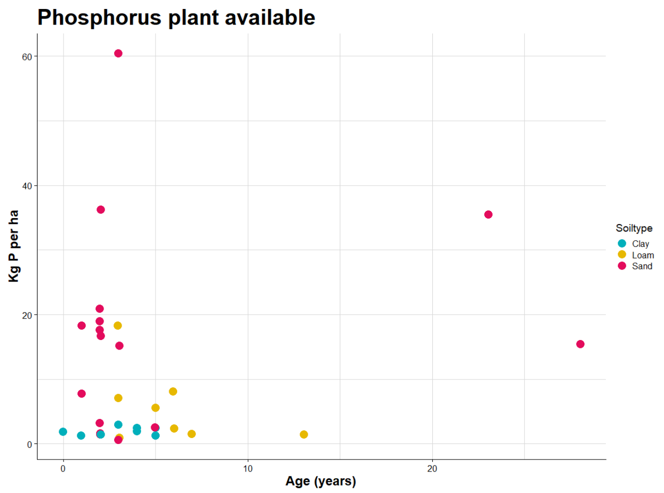
Annex figure 2. Plot by forest age of belowground organic carbon stock in 0-25cm of the soil, in Mg per ha. N=25. Soil type is visualized in point color; blue = clay, yellow = loam, pink = sand.

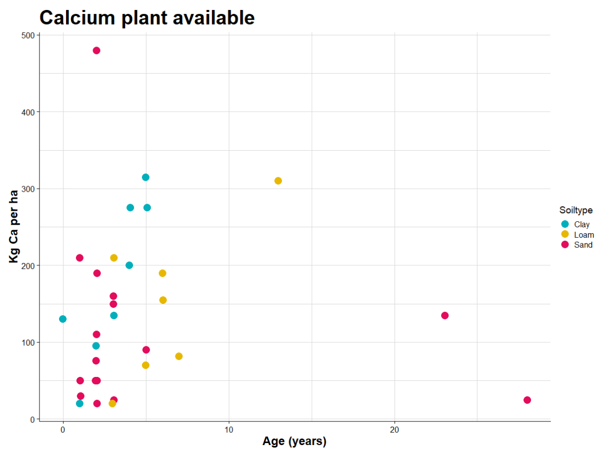
Food forest	Mg SOC ha-1 (0-25cm)	Average soil compaction 0-22,5 cm in psi
Ketelbroek	31,17222599	123,8095267
Sualmana	32,9025	152,2083333
Eemvallei Zuid	63,16786158	179,8494667
Houtrak	95,68654661	111,5699033
Thuishaven	53,98730085	255,0893
Roggebotstaete	45,03350847	140,1333433
Amsterdam	80,22478531	198,6666667
De Overtuin	85,87025424	120,81162
Benthuizen	69,86828708	163,0877467

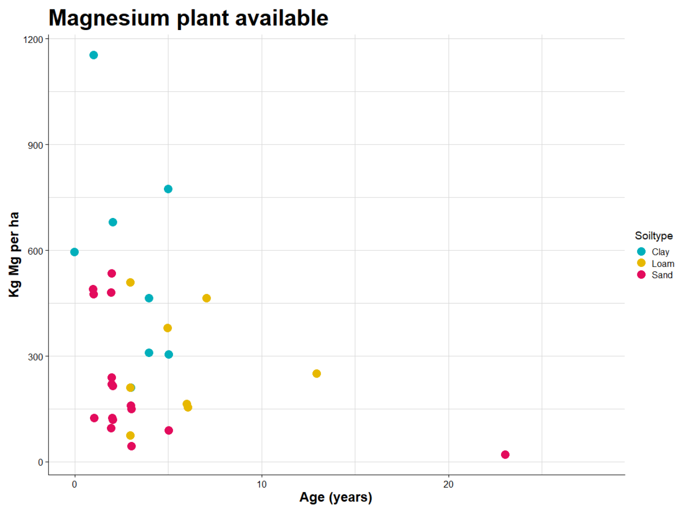
Droevendaal	26,27523305	163,8461833
Schijndel Boschweg	24,3826589	107,3333233
Den Food Bosch	51,11864407	93,16805667
De Terp	38,080625	228,4516333
Nij Boelens	49,80994915	106,5161333
Binnenbos	41,16025424	179,5269067
Kreilerwoud	70,17802754	73,98149333
Laakoever	88,65330508	132,91111
Het Loonse Bos	41,36080508	213,99999
Heische Hoeve	57,16584746	235,5555567
De Pullenhap	34,03601695	115,8889
Ruurhoeve	46,27118644	162,5
Woensdrecht	37,94194915	96,83333333
Schevichoven	63,43050847	174,1875
Groengenoten	27,97751271	218,9840967
Lekker Landgoed	78,39189619	111,6773933

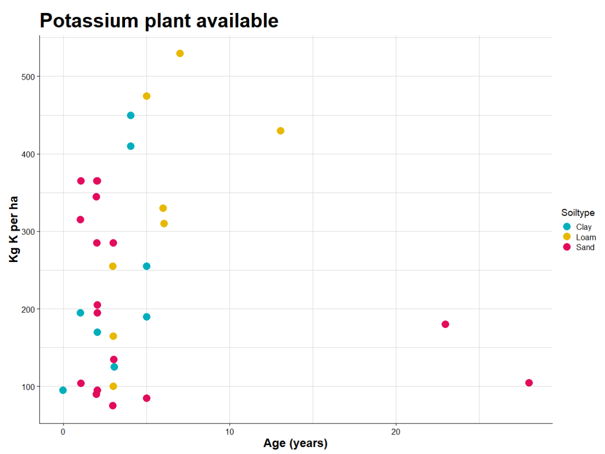
Annex table 2. Soil organic carbon in the top 25cm soil and average soil compaction in the top 52,5 cm of the soil, per food forest (n=25)

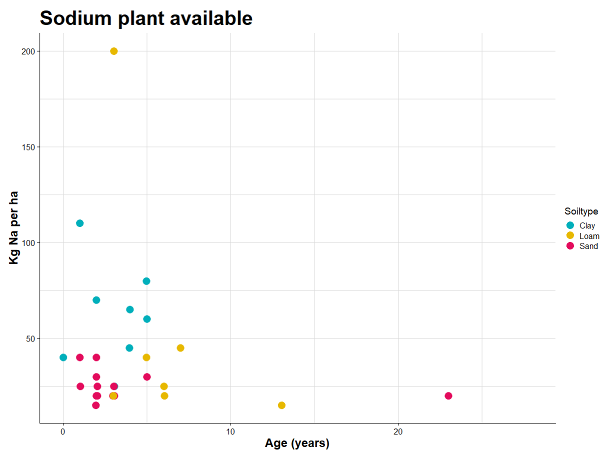




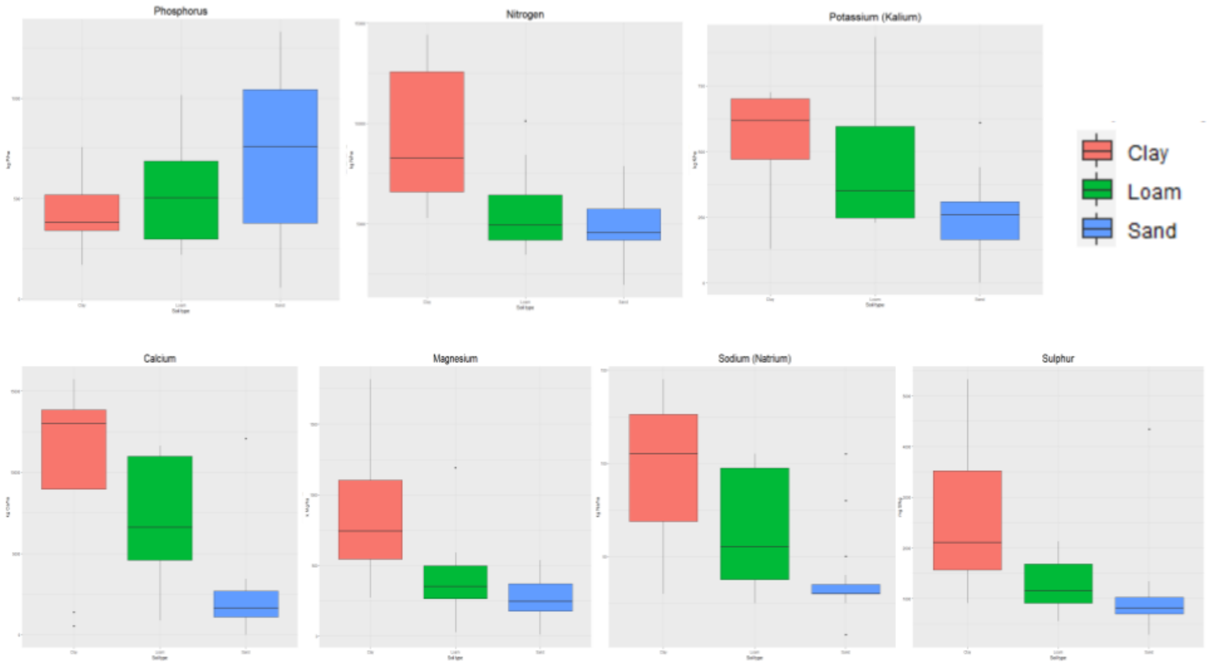




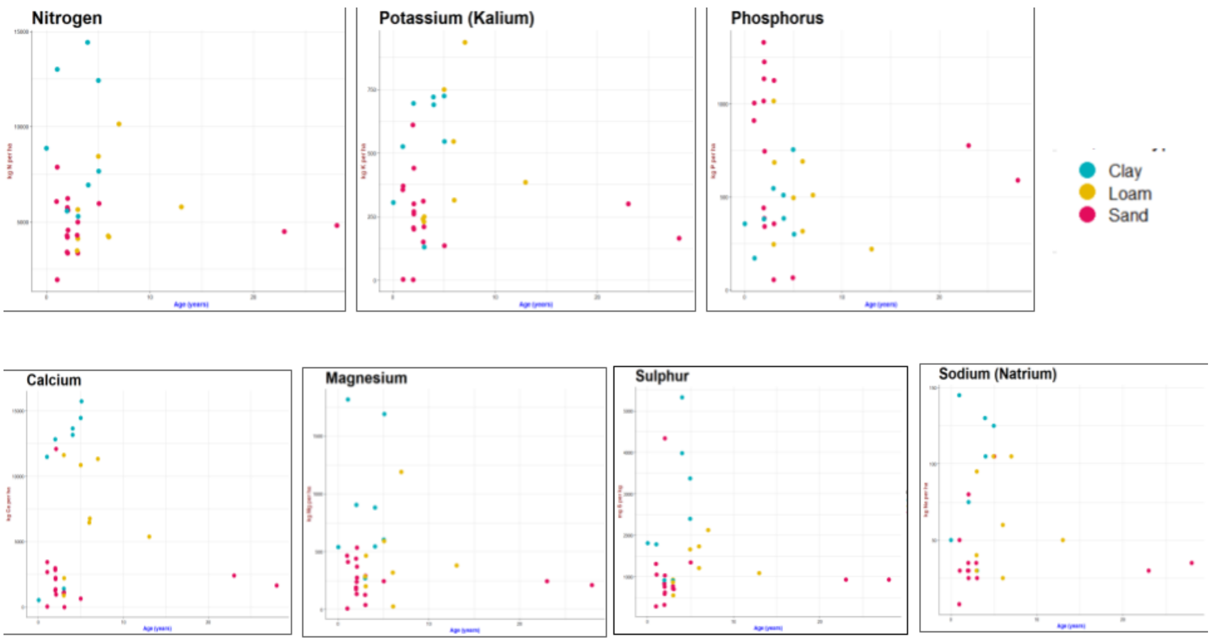




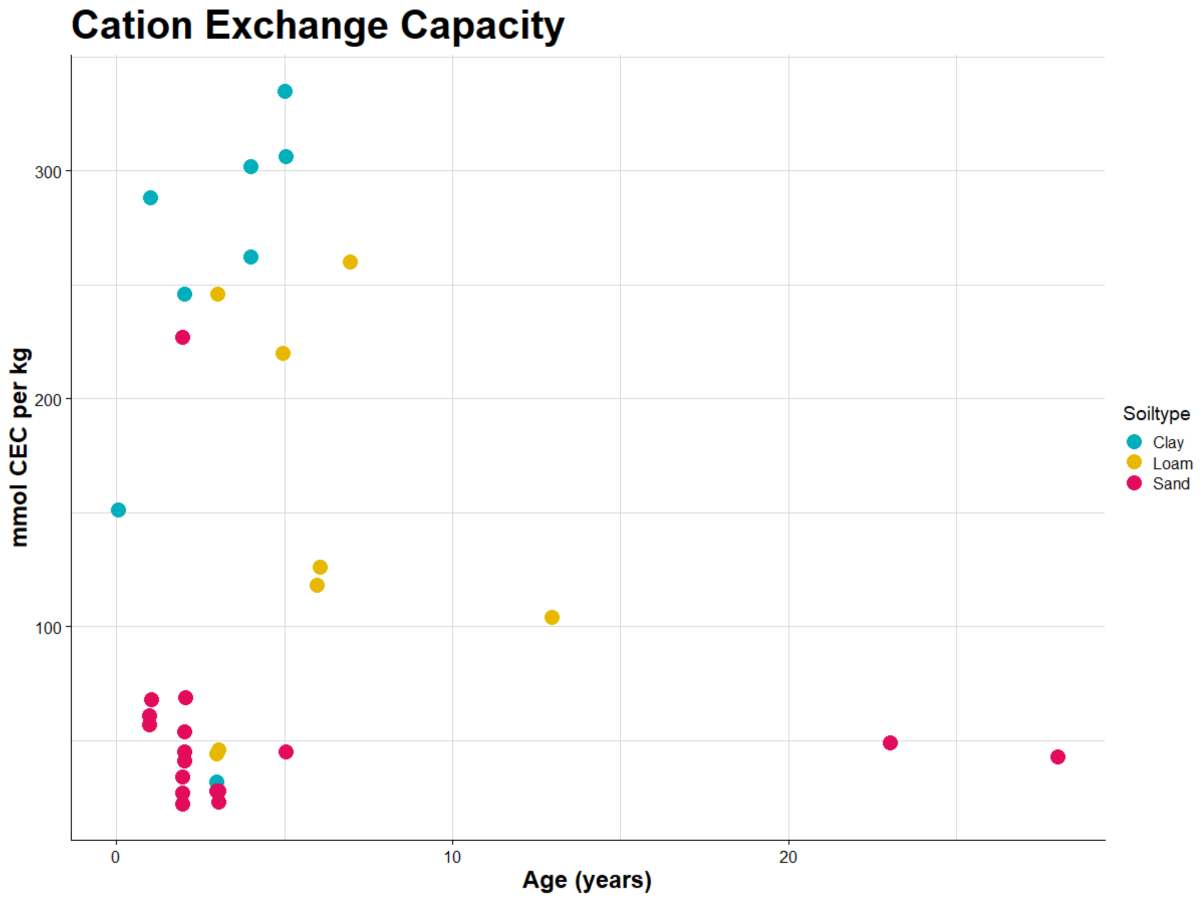
Annex figure 3. a,b,c,d,e,f,g. Time series for plant available primary (N,P,K) and secondary (Mg,S,Ca) nutrients, and sodium (Na), by age (years). Blue = clay, yellow = loam, Pink = sand. For statistics on macronutrient - age, please refer to the summary table (table x).



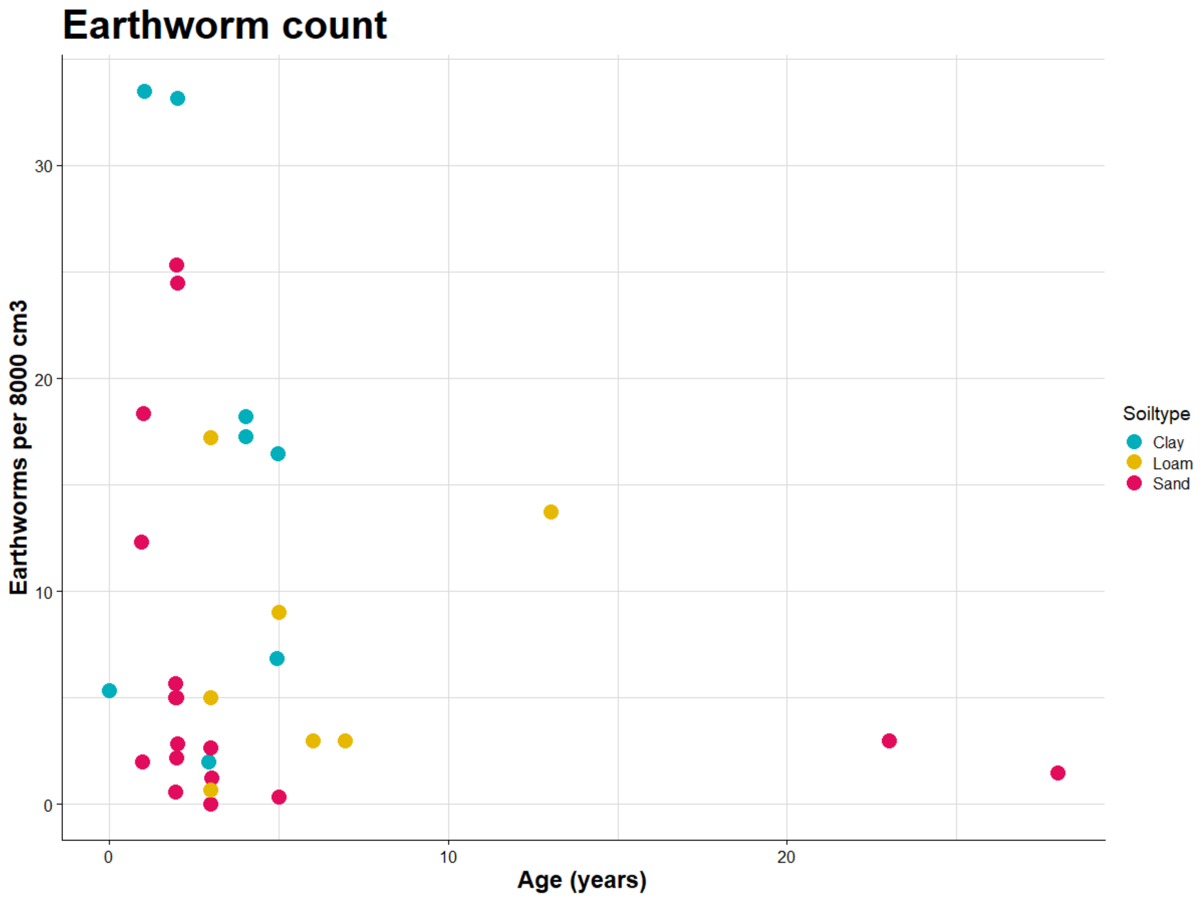
Annex fig 4 a,b,c,d,e,f,g.. Boxplot visualizations of the differences in concentration of non-plant accessible soil stock macronutrients per soil type. Left to right, top to bottom: phosphorus, nitrogen, potassium, calcium, magnesium, sodium and sulfur.



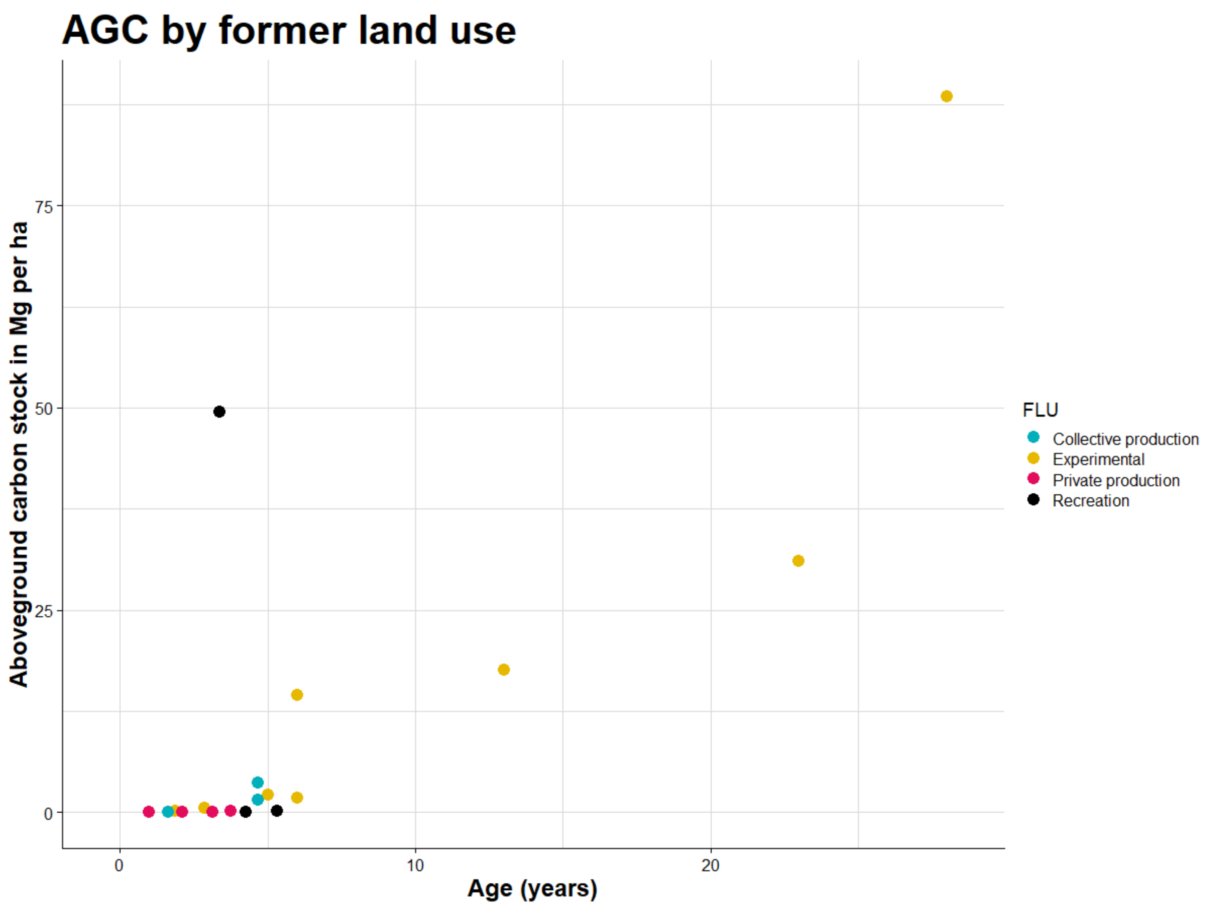
Annex figure. 5 a,b,c,d,e,f,g., scatterplots of the concentration of soil macronutrients (y axis) plotted against food forest age in years (x axis). Left to right, top to bottom: nitrogen, potassium (kalium), phosphorus, calcium, magnesium, sulfur, sodium (natrium).



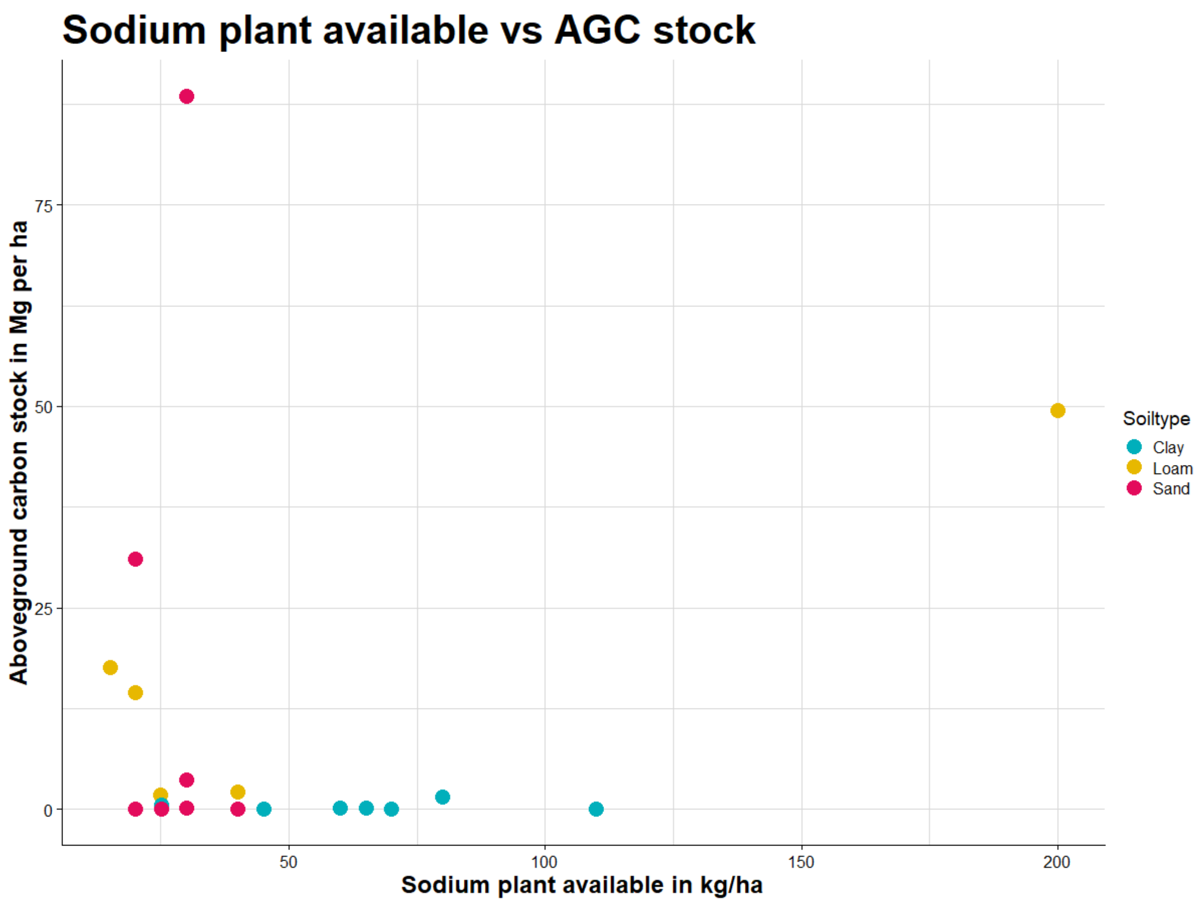
Annex figure 6. Time series of Cation Exchange Capacity in mmol per kg. N=33. Soil type is visualized in point color; blue = clay, yellow = loam, pink = sand.



Annex figure 7. Plot by forest age of earthworms per 8000 cm3. N=33. Soil type is visualized in point color; blue = clay, yellow = loam, pink = sand.

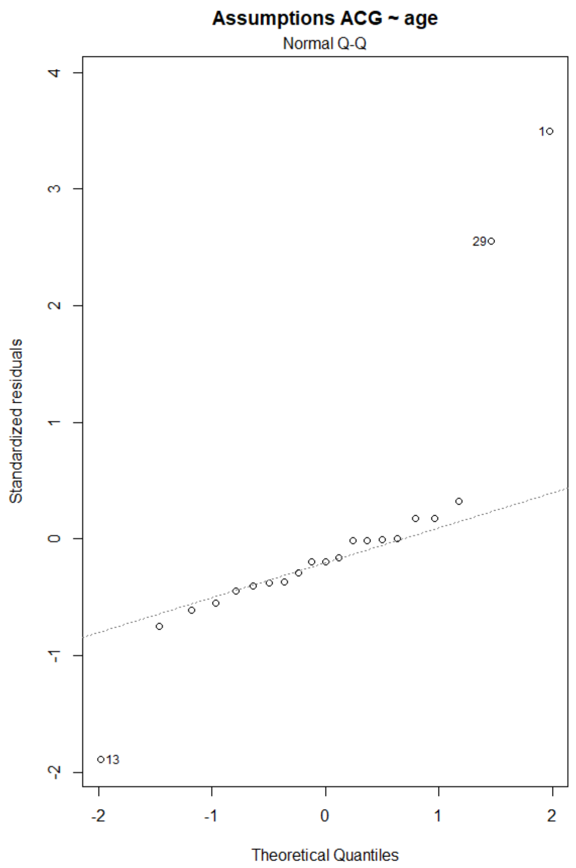


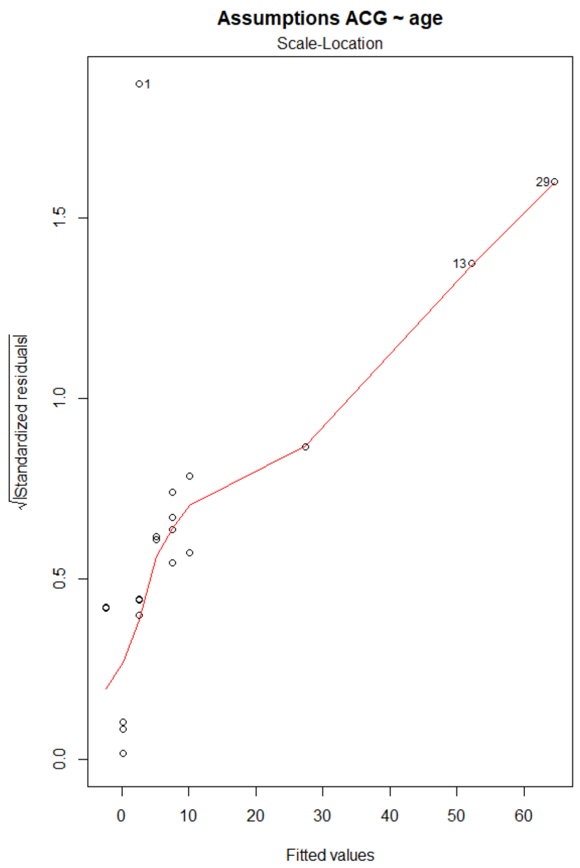
Annex figure 8. Time series of Aboveground Carbon Stock in Mg per ha. N=22. Former land use (FLU) is visualized in the color of the points; blue = collective production, yellow = experimental , pink = private production , black = recreation

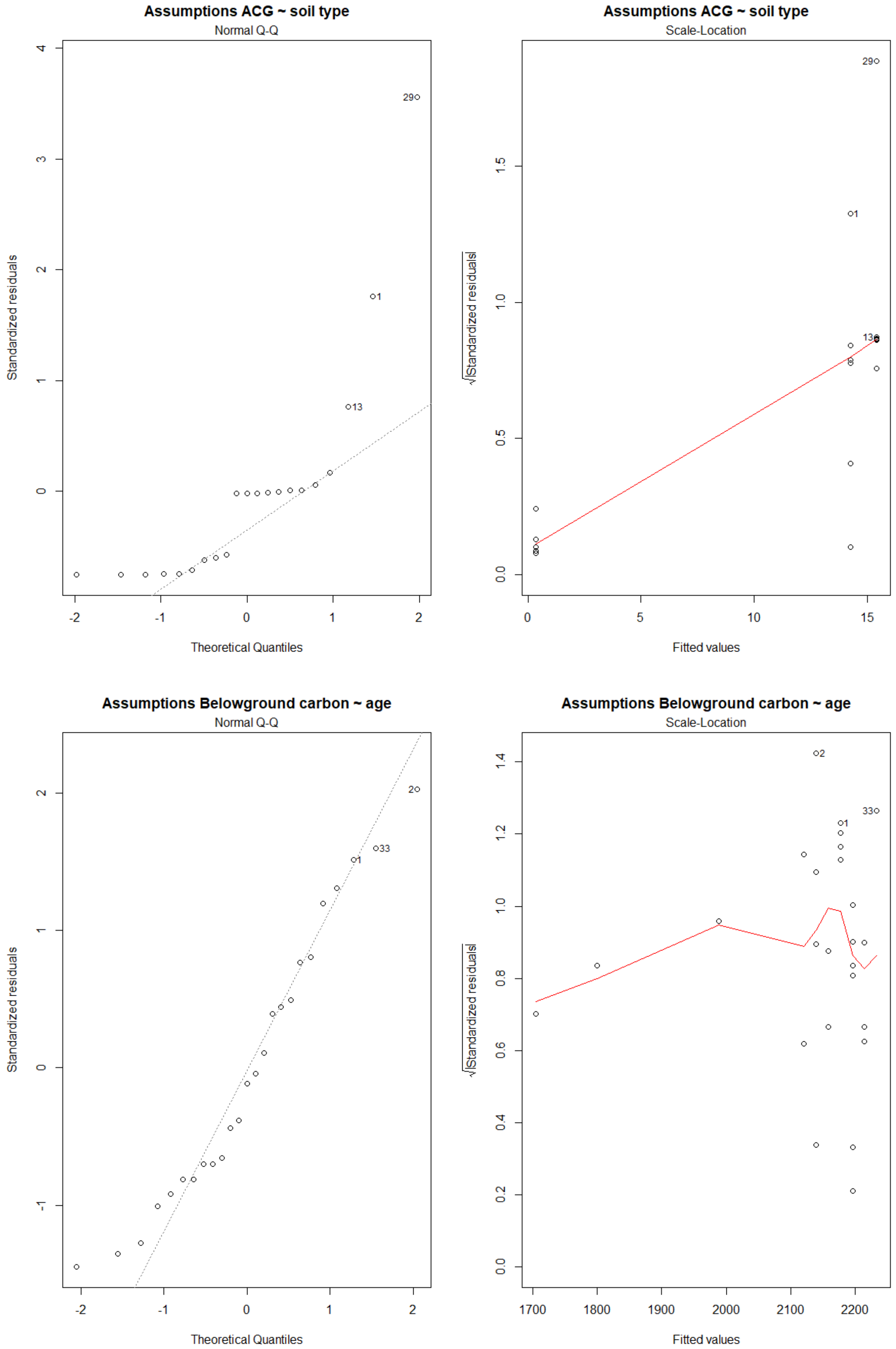


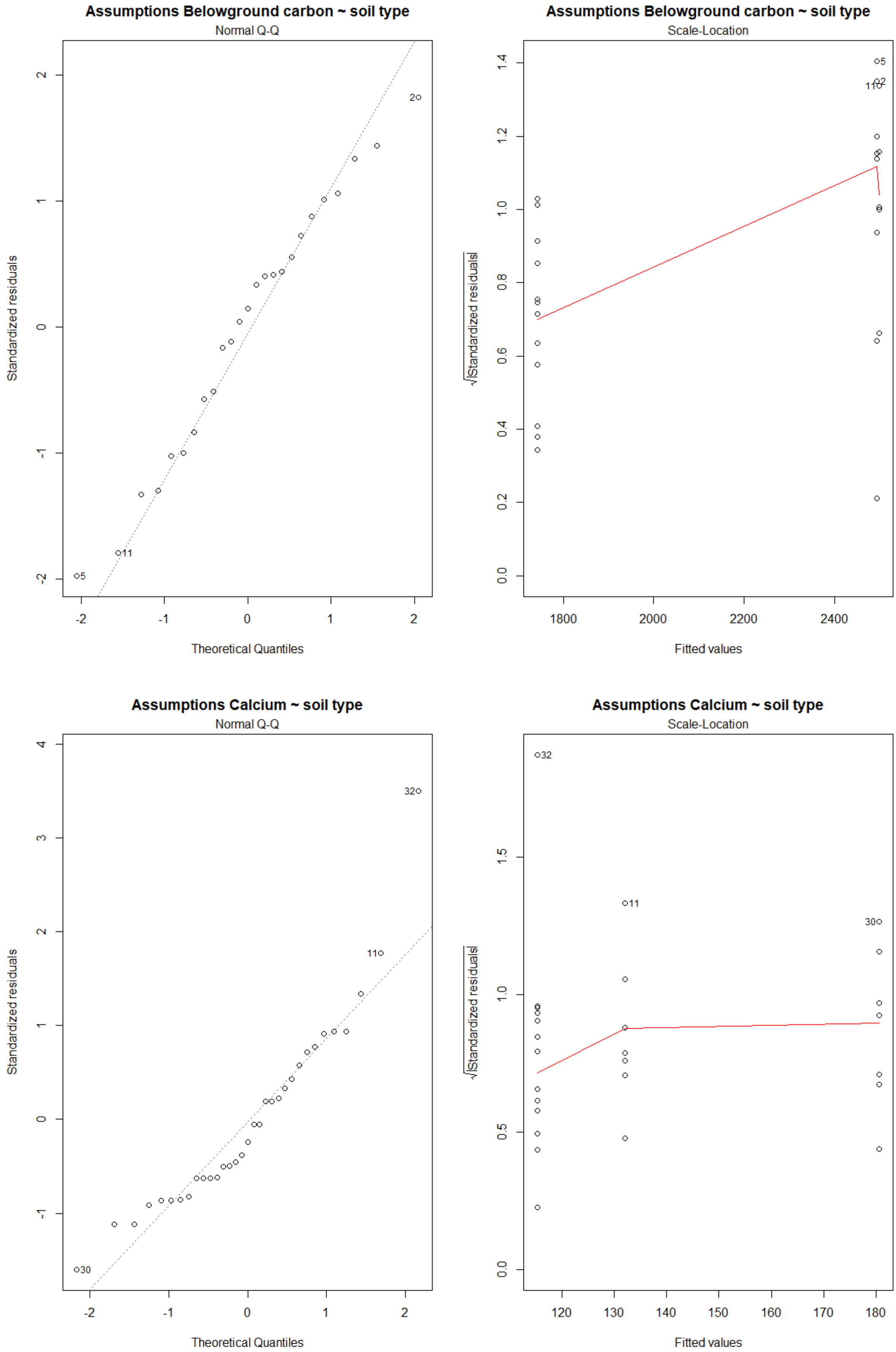
Annex Figure 9. Plant-available sodium (kg/ha) versus Aboveground carbon stock (Mg/ha). N=22. Soil type is visualized in point color; blue = clay, yellow = loam, pink = sand.

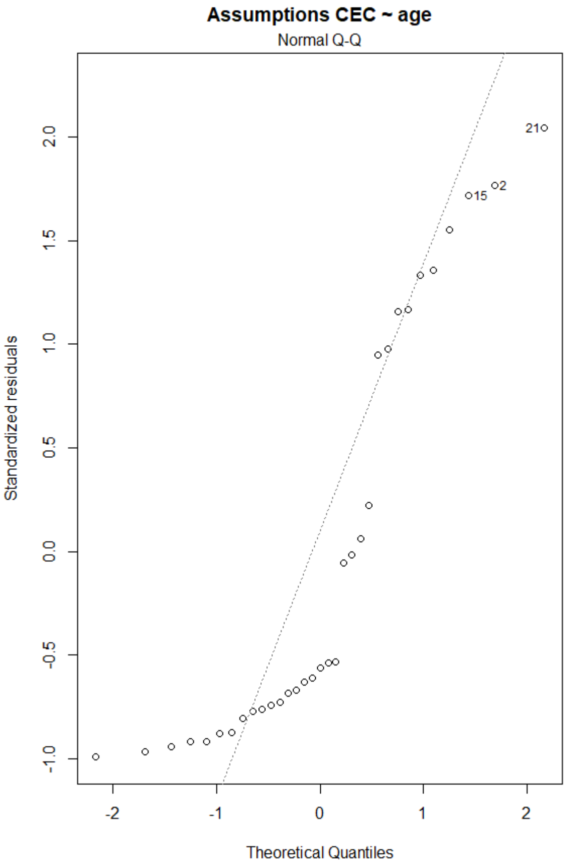
Annex: diagnostics of statistical analyses

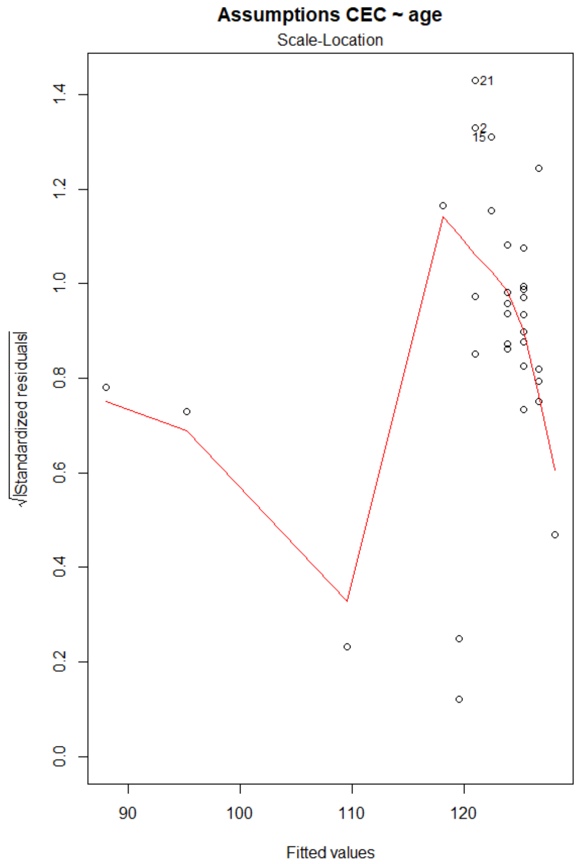


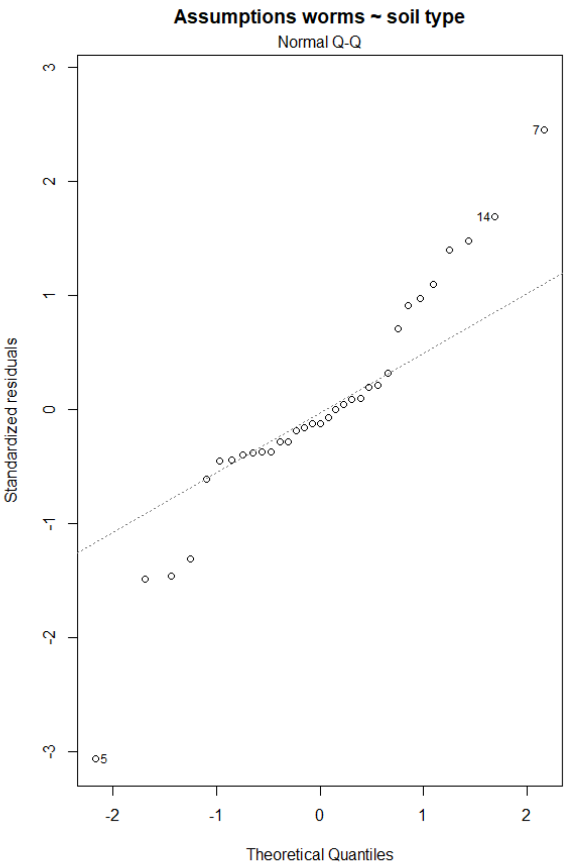


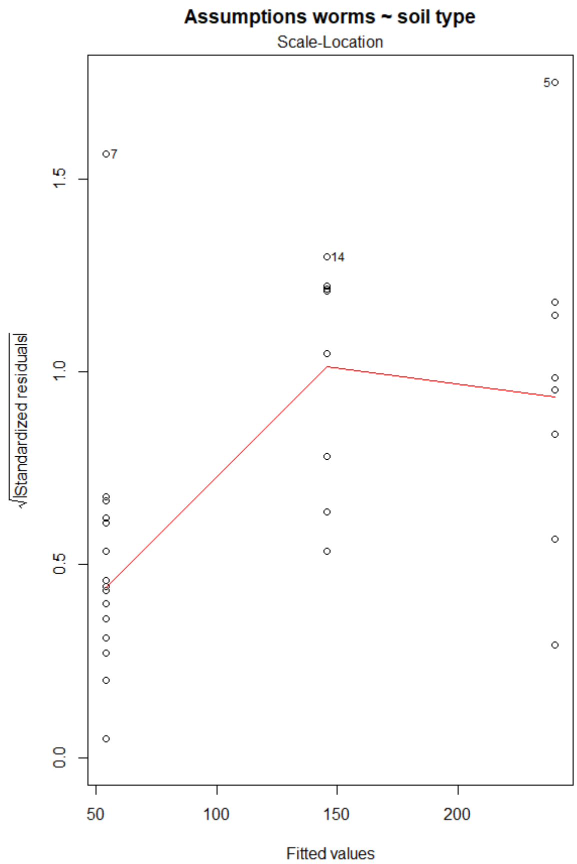

Assumptions ACG ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Assumptions ACG ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
Assumptions Belowground carbon ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Assumptions Belowground carbon ~ age
Scale-Location
√|Standardized residuals|
Fitted values

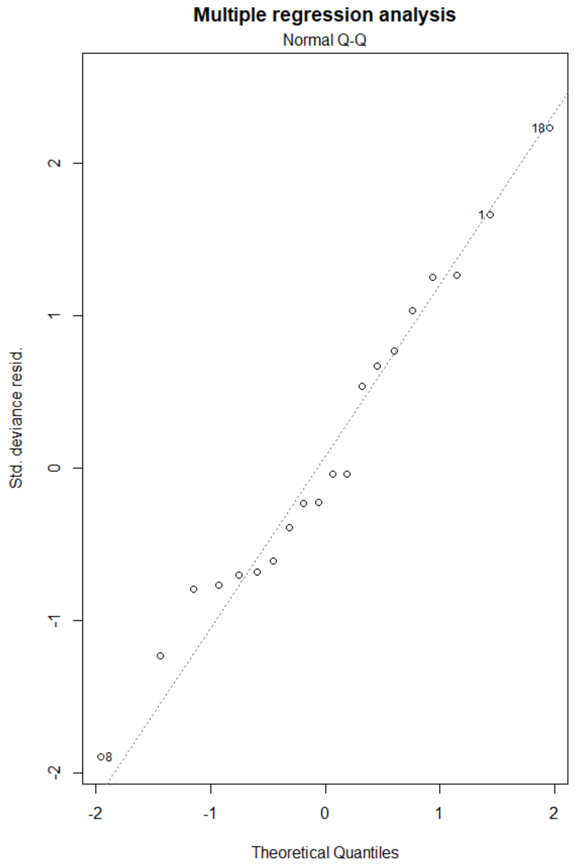

Assumptions Belowground carbon ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Assumptions Belowground carbon ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
Assumptions Calcium ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Assumptions Calcium ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values

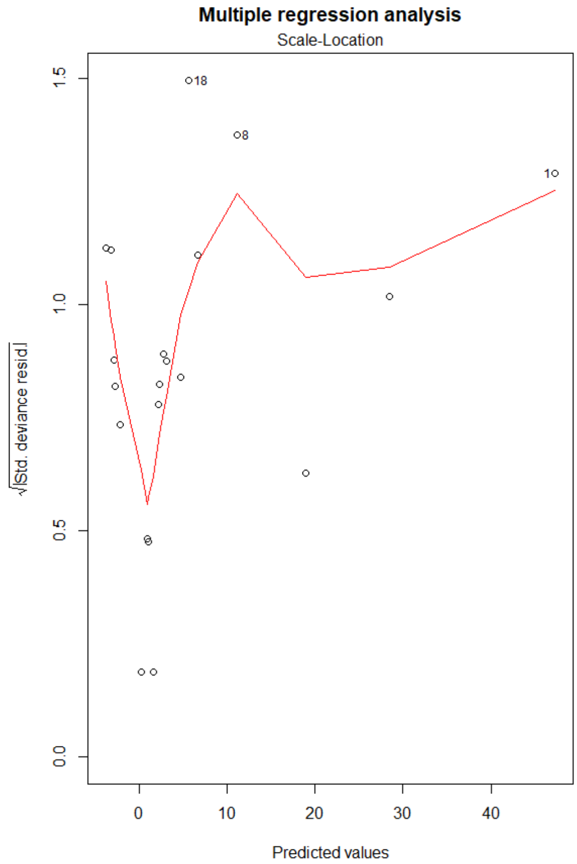

Assumptions CEC ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
21
15
2

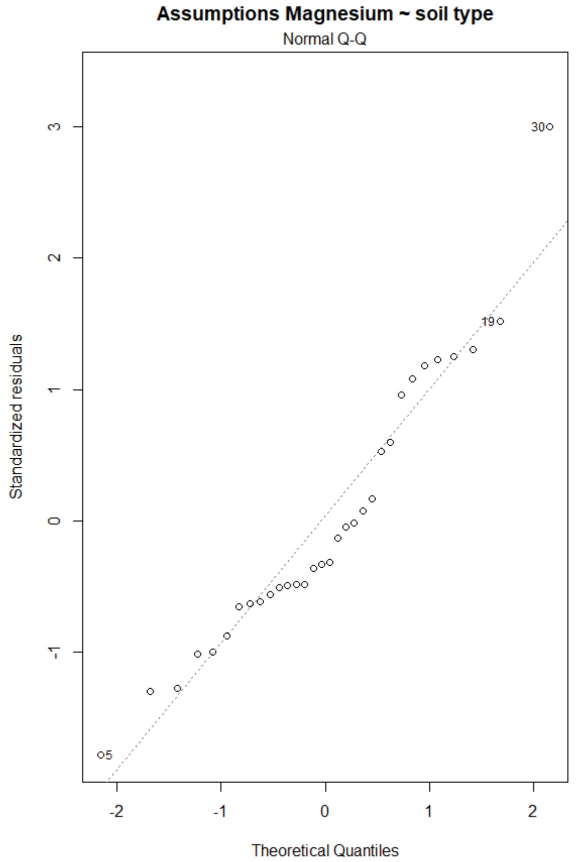

Assumptions CEC ~ age
Scale-Location
√|Standardized residuals|
Fitted values
21
2
15

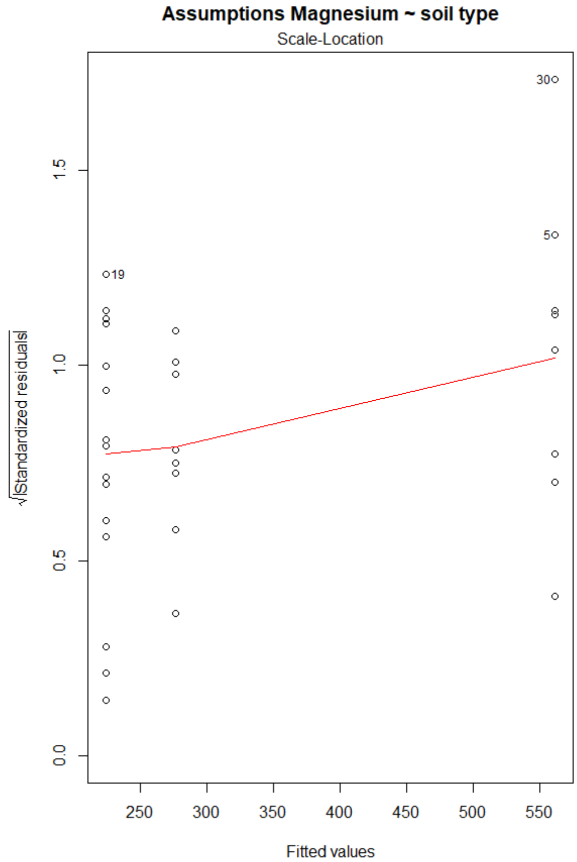

Assumptions worms ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
7
14
5

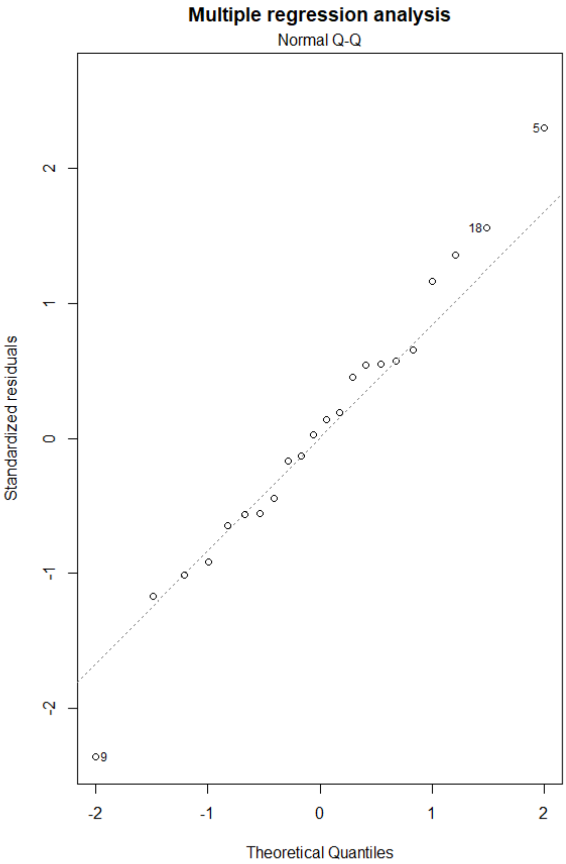

Assumptions worms ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
5
7
14

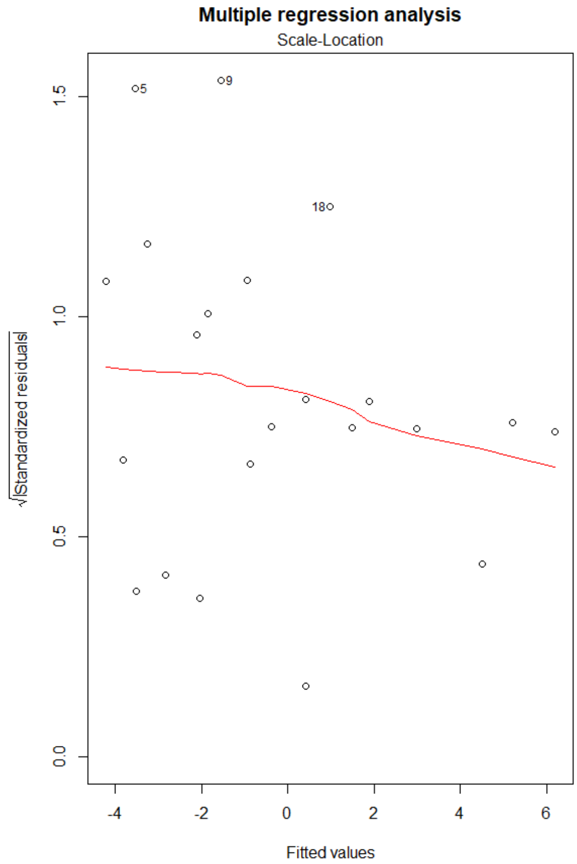

Multiple regression analysis
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
18
1
8

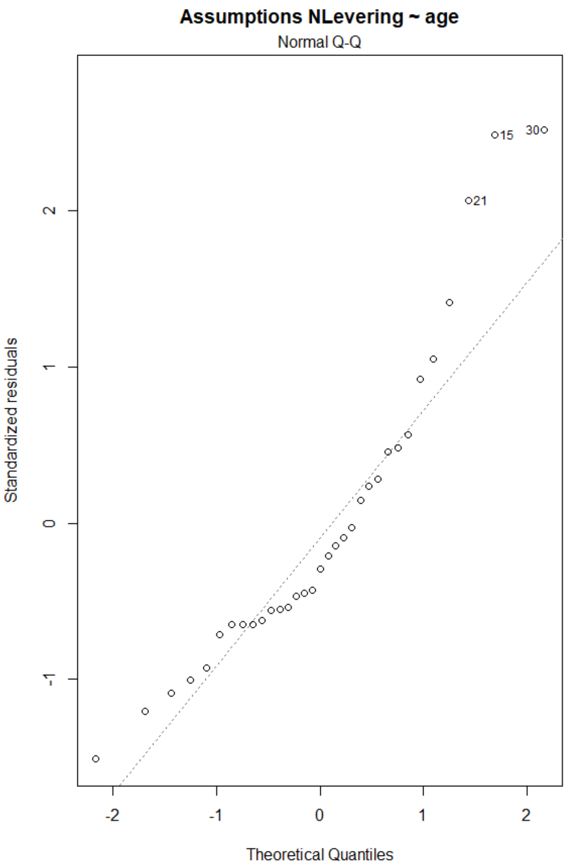

Multiple regression analysis
Scale-Location
√|Std. deviance resid.|
Predicted values
18
8
1

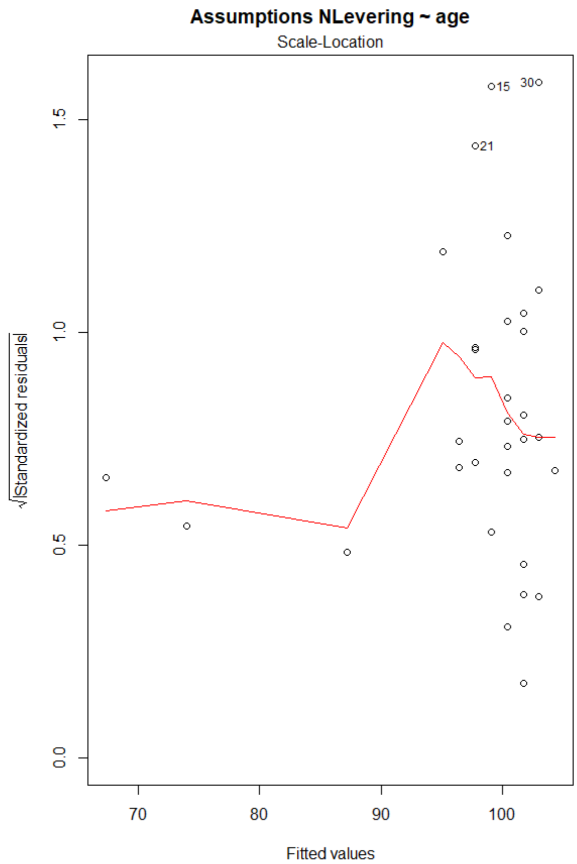

Assumptions Magnesium ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
30
19
5

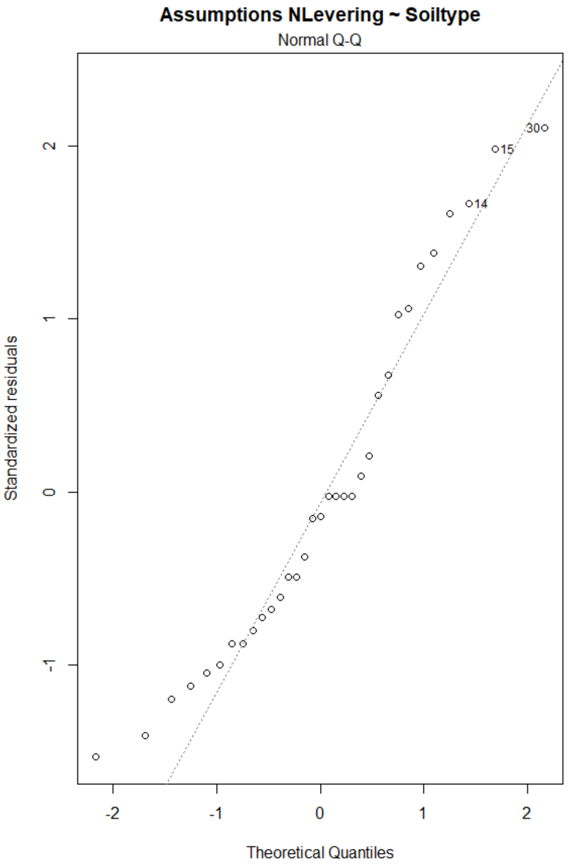

Assumptions Magnesium ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
30
5
19

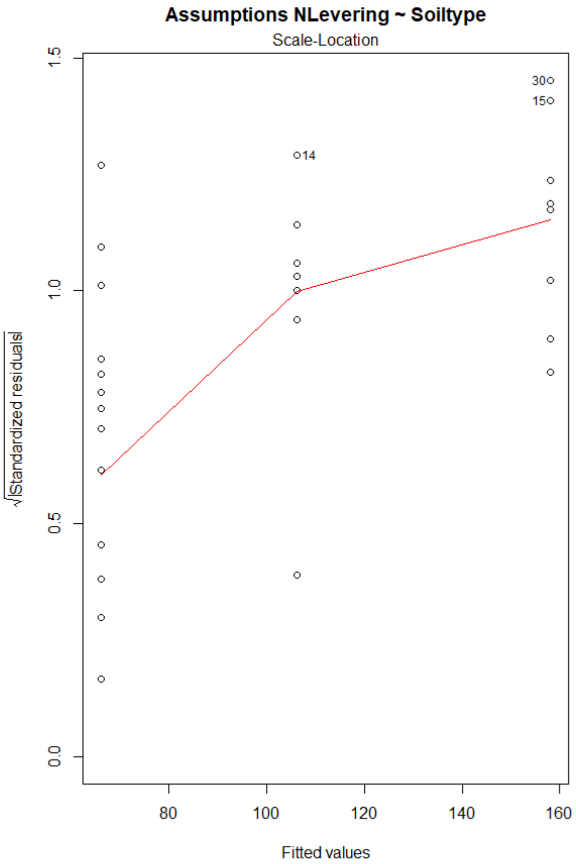

Multiple regression analysis
Normal Q-Q
Standardized residuals
Theoretical Quantiles
5
18
9

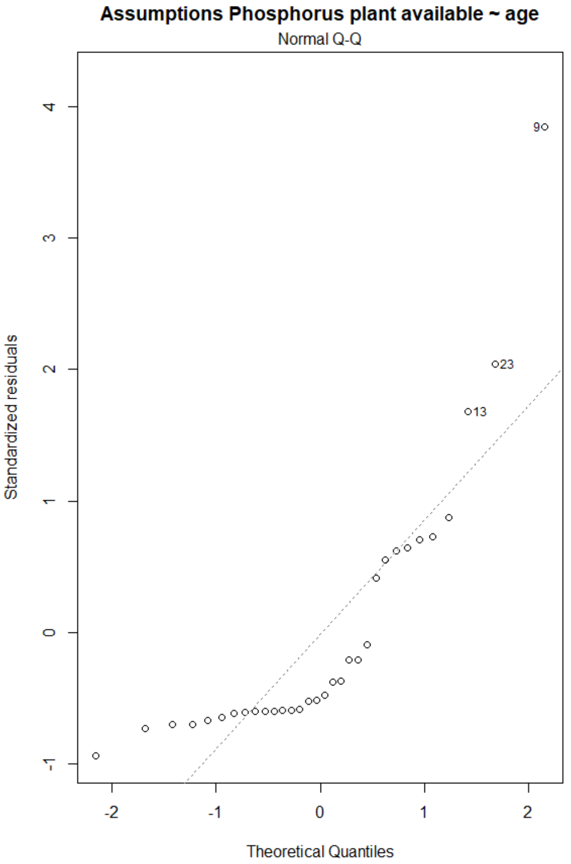

Multiple regression analysis
Scale-Location
√|Standardized residuals|
Fitted values
5
9
18

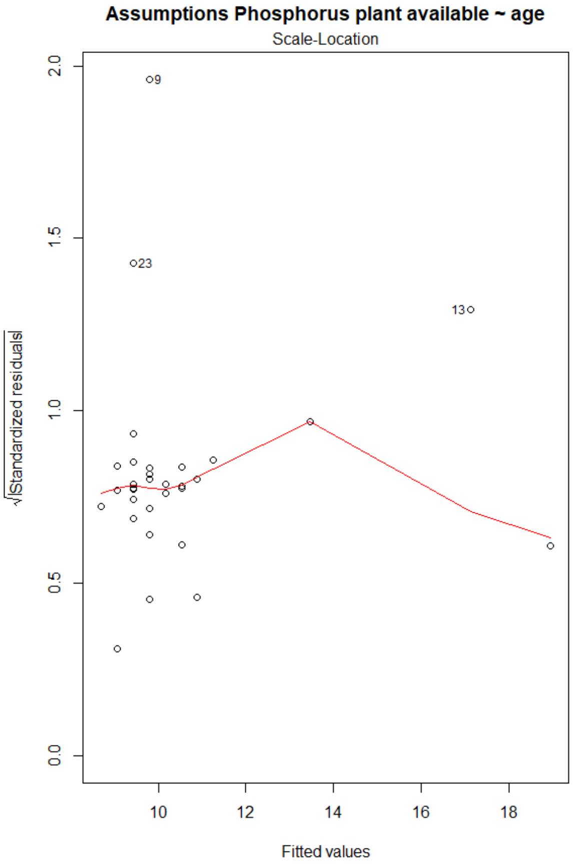

Assumptions NLevering ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
15
30
21

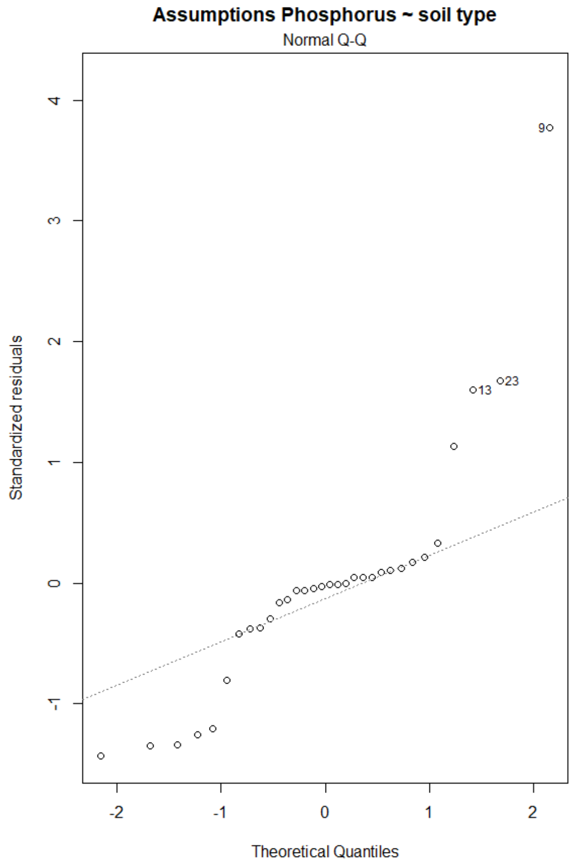

Assumptions NLevering ~ age
Scale-Location
√|Standardized residuals|
Fitted values
15
30
21

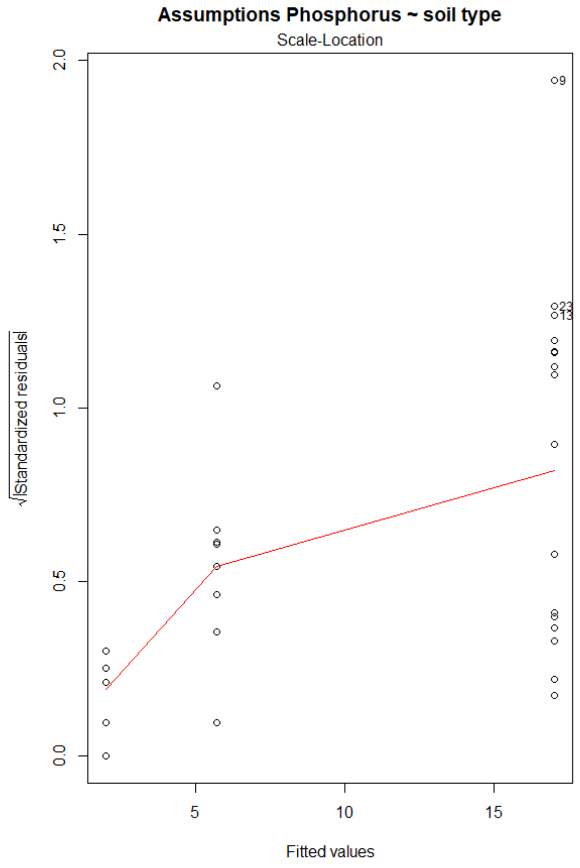

Assumptions NLevering ~ Soiltype
Normal Q-Q
Standardized residuals
Theoretical Quantiles
30
15
14

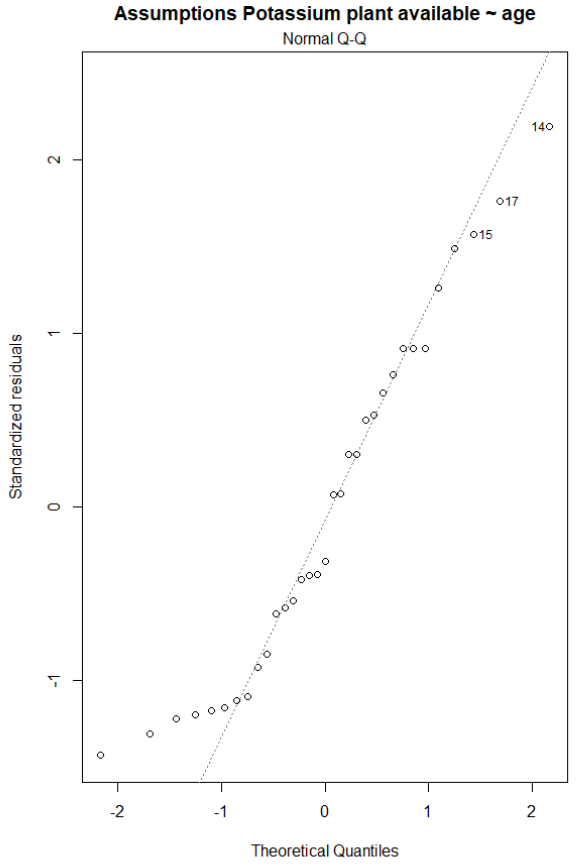

Assumptions NLevering ~ Soiltype
Scale-Location
√|Standardized residuals|
Fitted values
30
15
14

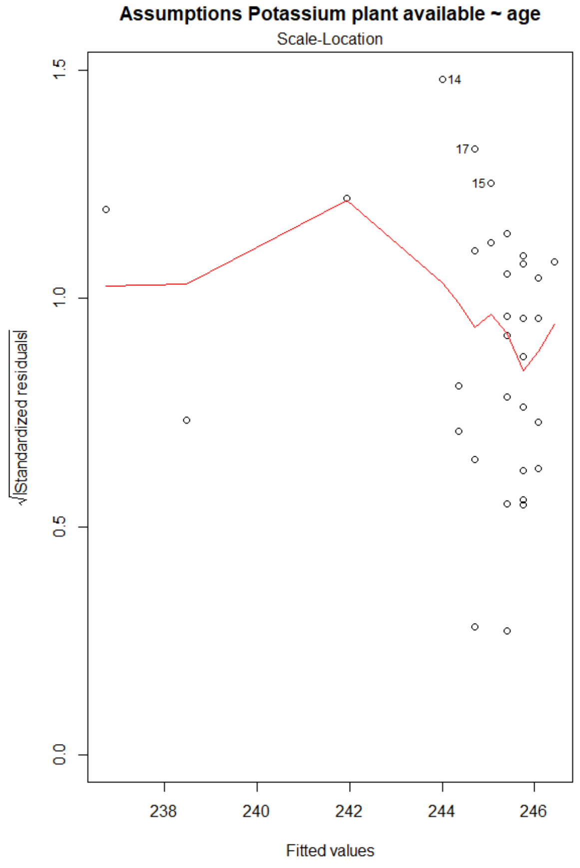

Assumptions Phosphorus plant available ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
9
23
13

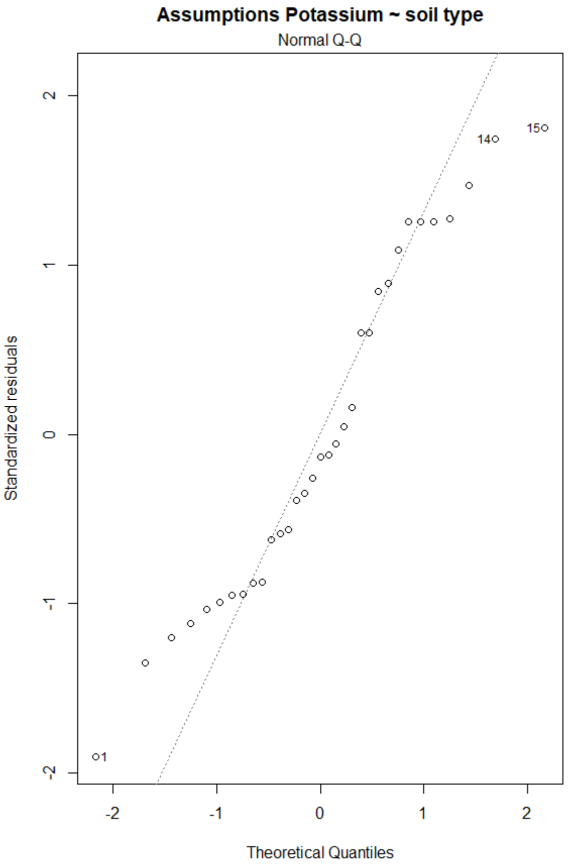

Assumptions Phosphorus plant available ~ age
Scale-Location
√|Standardized residuals|
Fitted values
9
23
13

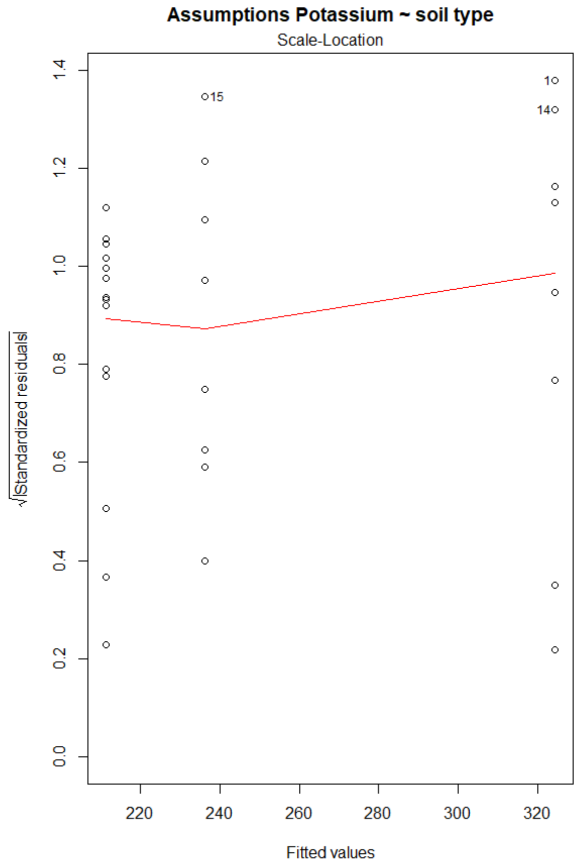

Assumptions Phosphorus ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
9
13
23

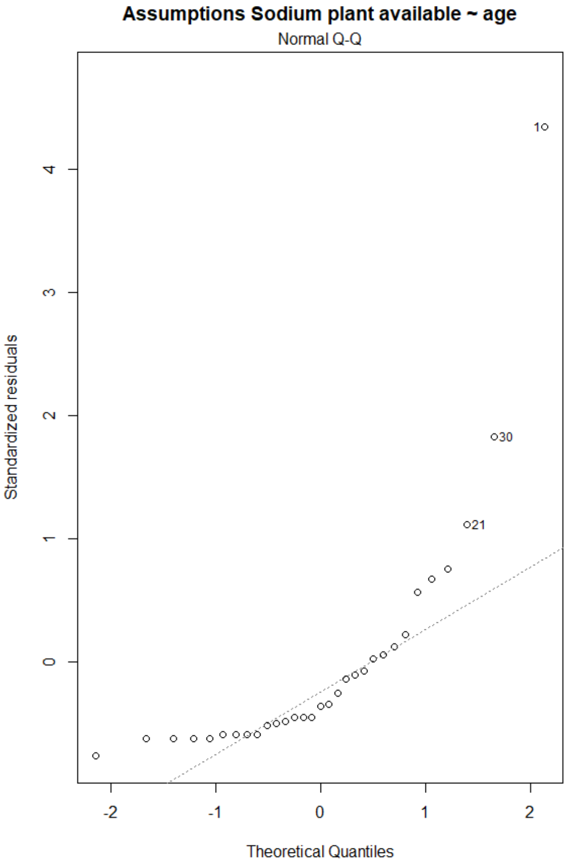

Assumptions Phosphorus ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
9
23
13

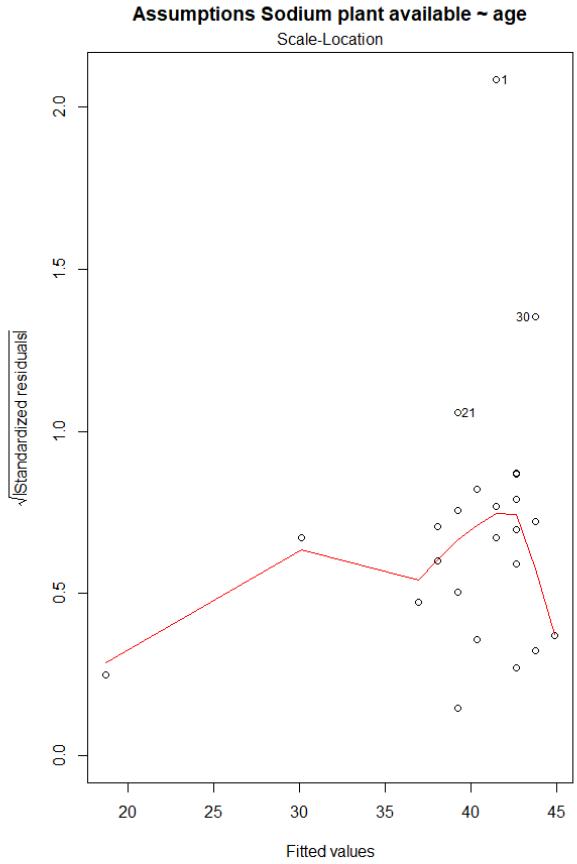

Assumptions Potassium plant available ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
14
17
15

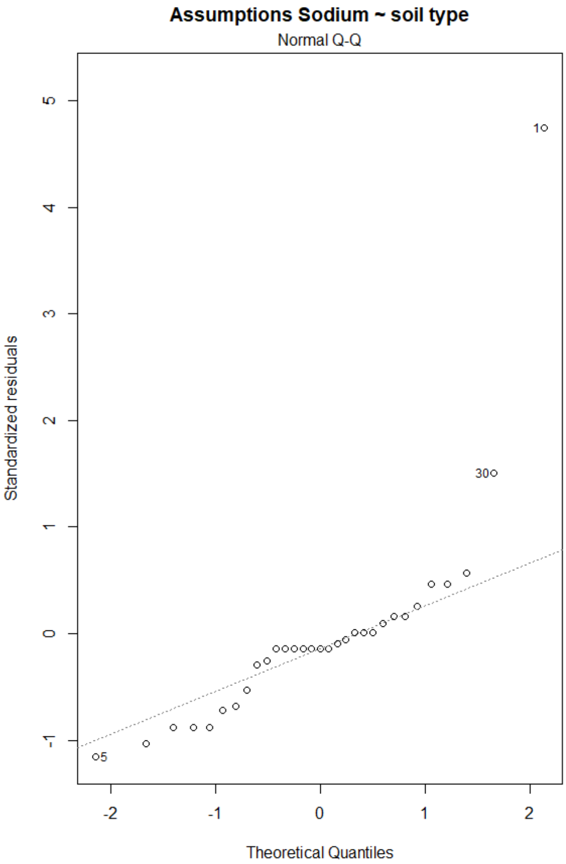

Assumptions Potassium plant available ~ age
Scale-Location
√|Standardized residuals|
Fitted values
14
17
15

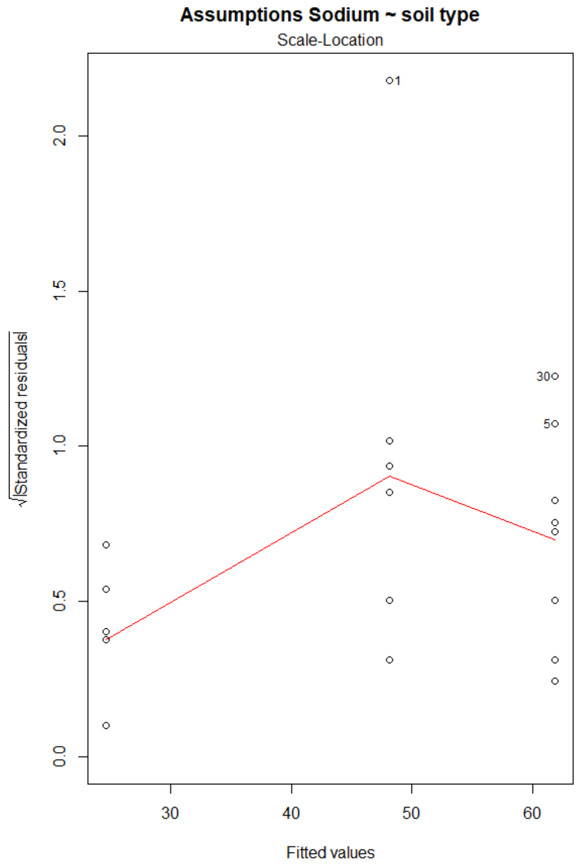

Assumptions Potassium ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
-2
-1
0
1
2
1
14
15

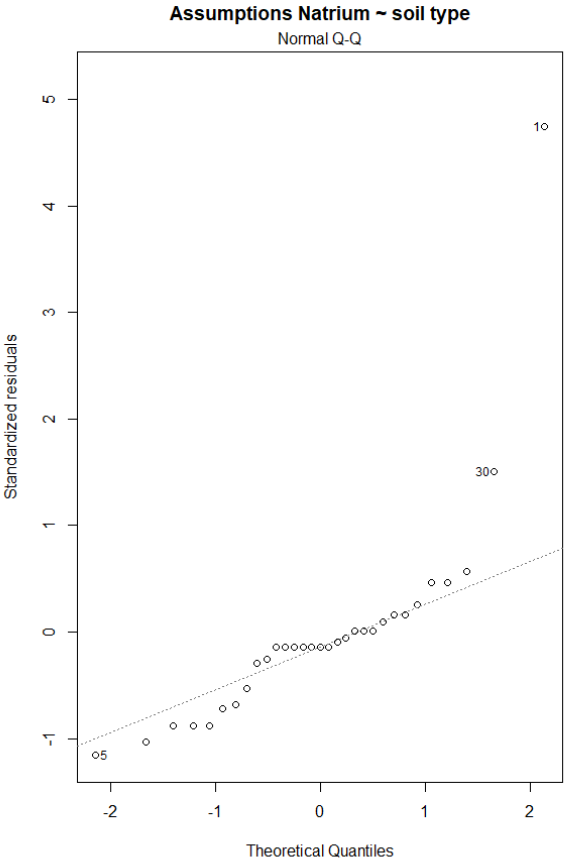

Assumptions Potassium ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
220
240
260
280
300
320
15
1
14

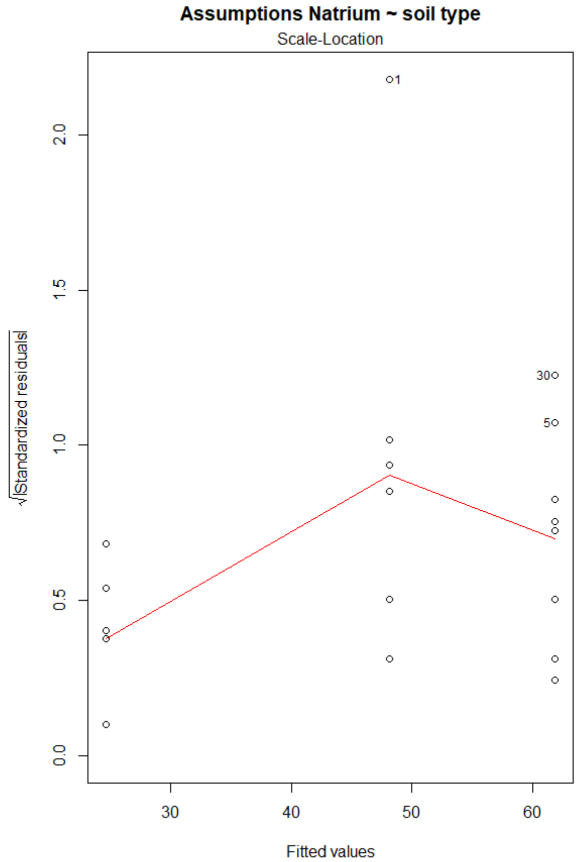

Assumptions Sodium plant available ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
0
1
2
3
4
-2
-1
0
1
2
1
30
21

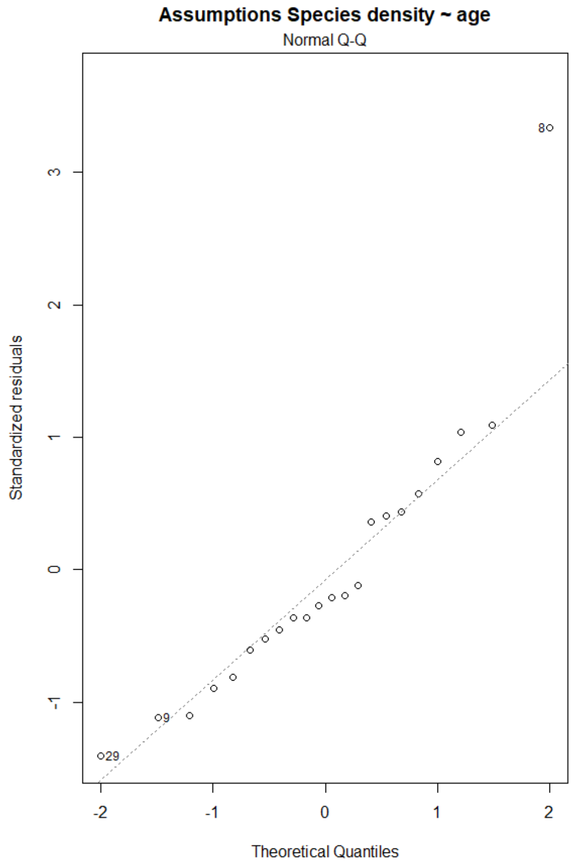

Assumptions Sodium plant available ~ age
Scale-Location
√|Standardized residuals|
Fitted values
0.0
0.5
1.0
1.5
2.0
20
25
30
35
40
45
1
30
21

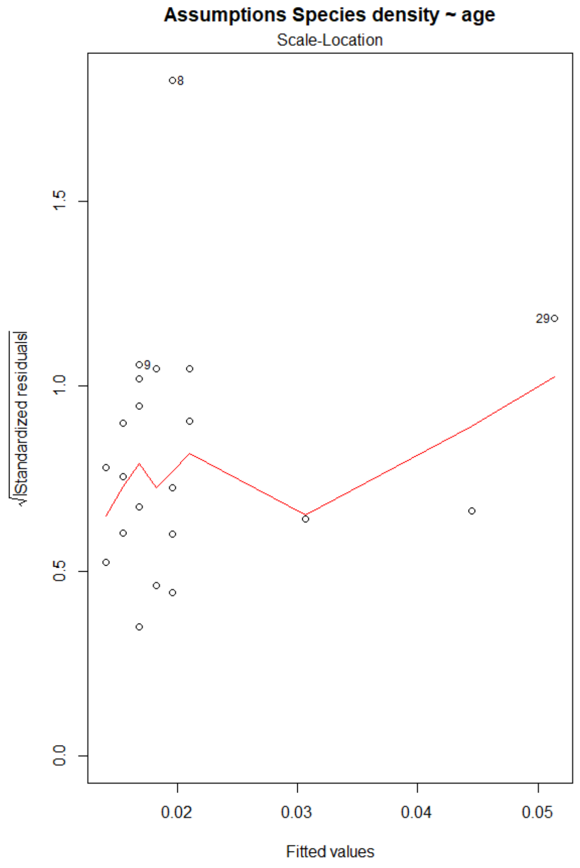

Assumptions Sodium ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
-2
-1
0
1
2
3
4
5
1
30
5

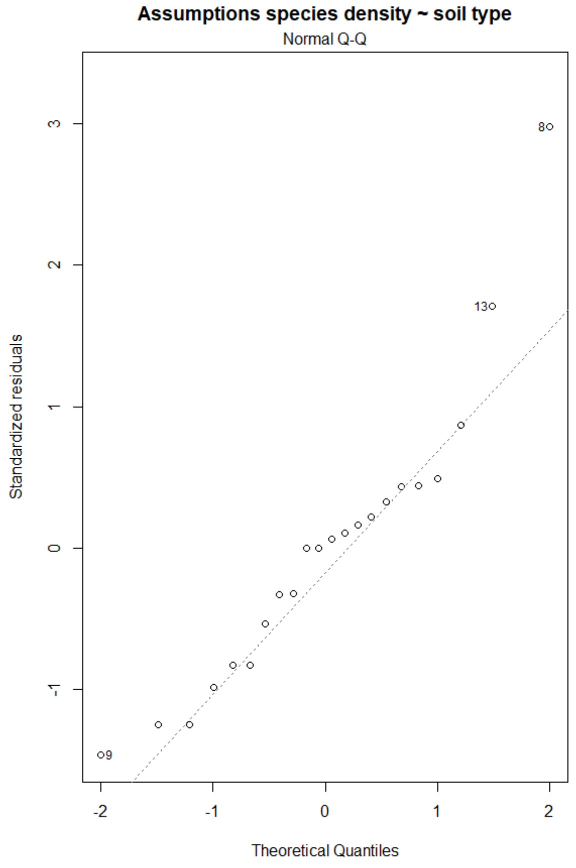

Assumptions Sodium ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
0.0
0.5
1.0
1.5
2.0
30
40
50
60
1
30
5

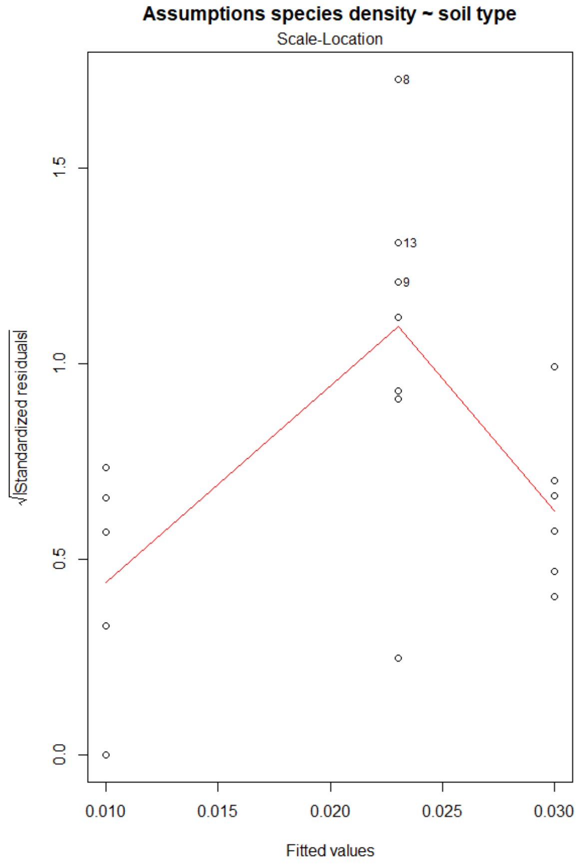

Assumptions Natrium ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
-2
-1
0
1
2
3
4
5
1
30
5

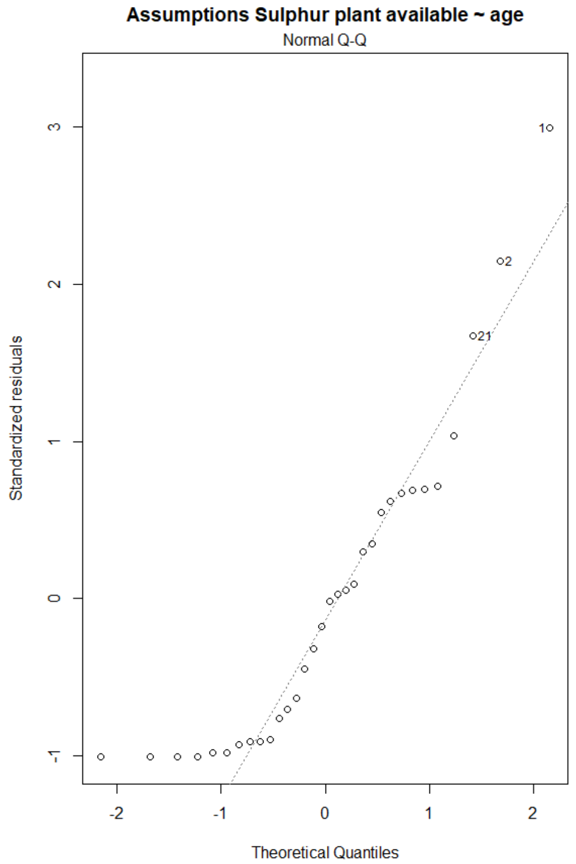

Assumptions Natrium ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
0.0
0.5
1.0
1.5
2.0
30
40
50
60
1
30
5


Assumptions Species density ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
8
9
29

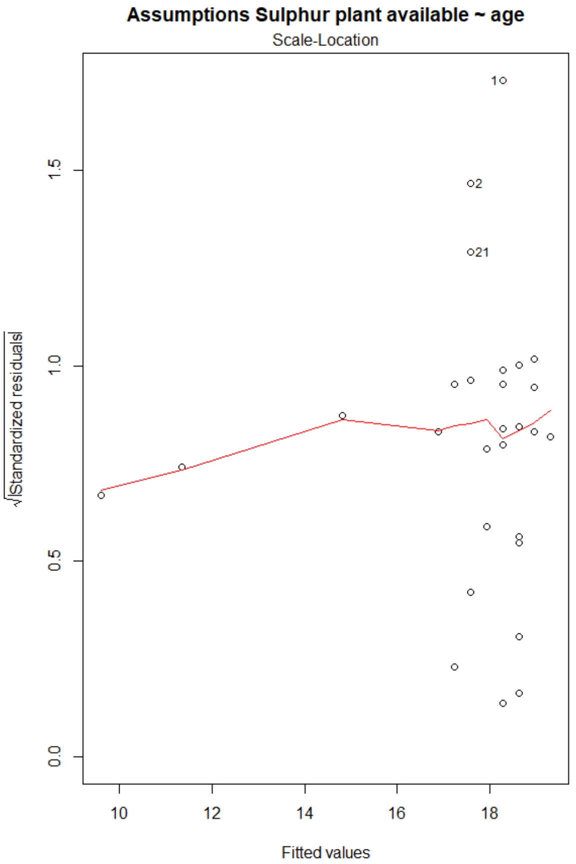

Assumptions Species density ~ age
Scale-Location
√|Standardized residuals|
Fitted values
8
29
9


Assumptions species density ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles
8
13
9

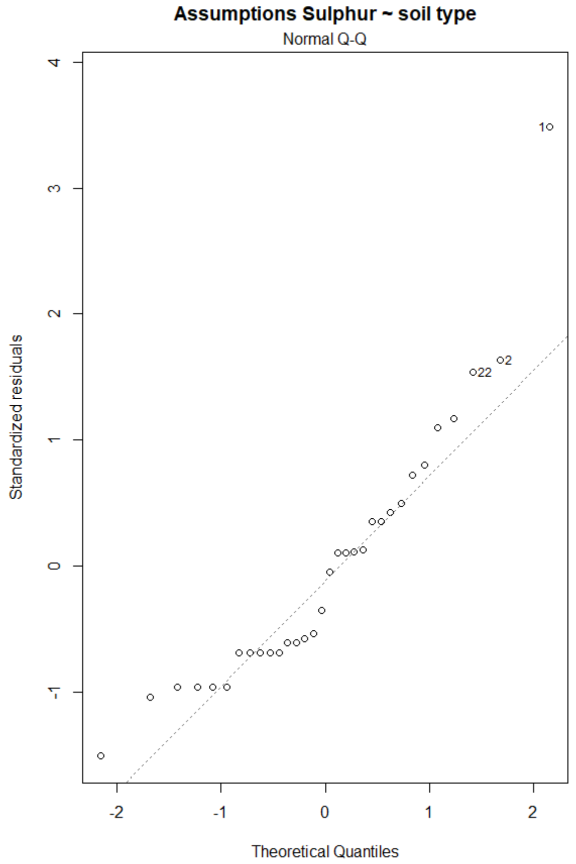

Assumptions species density ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values
8
13
9



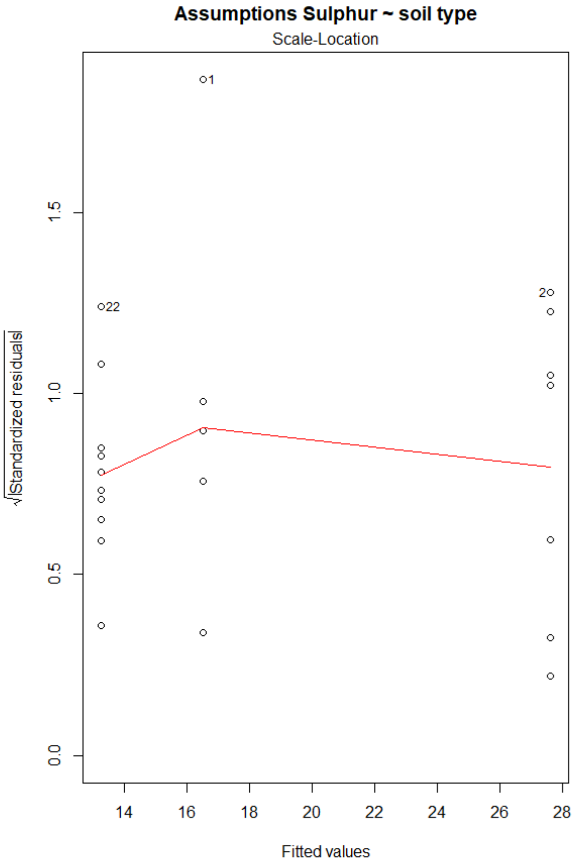
Assumptions Sulphur plant available ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles



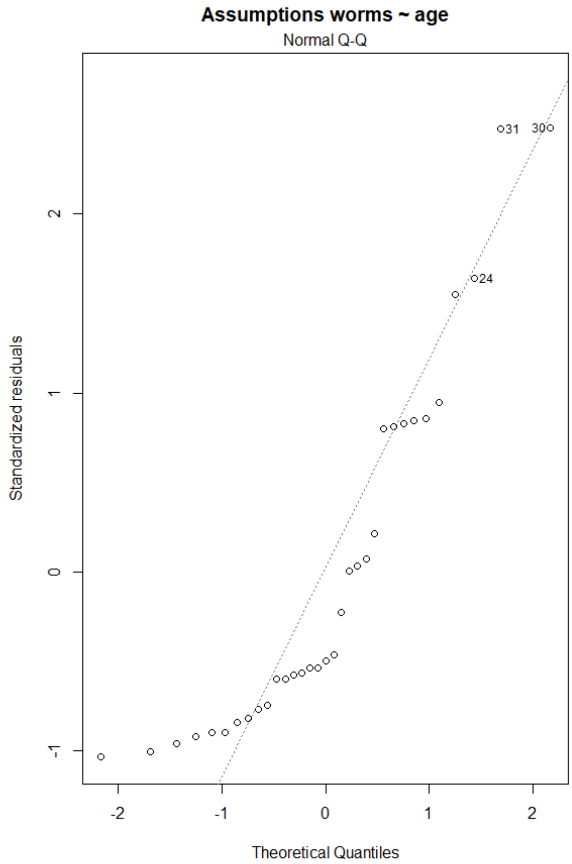
Assumptions Sulphur plant available ~ age
Scale-Location
√|Standardized residuals|
Fitted values

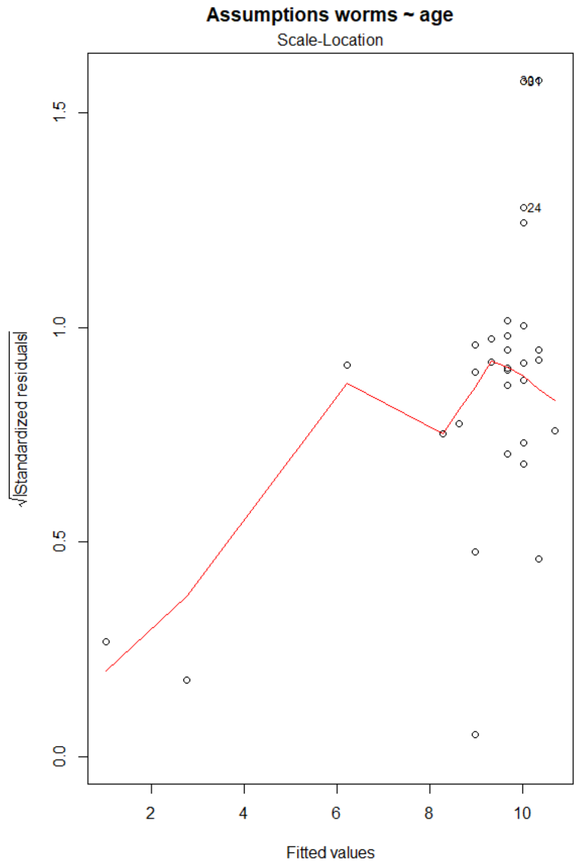


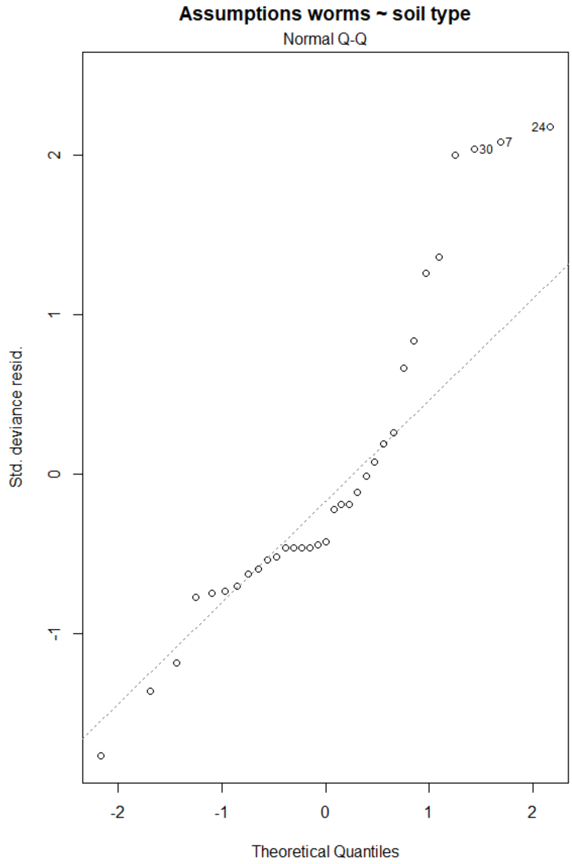
Assumptions Sulphur ~ soil type
Normal Q-Q
Standardized residuals
Theoretical Quantiles

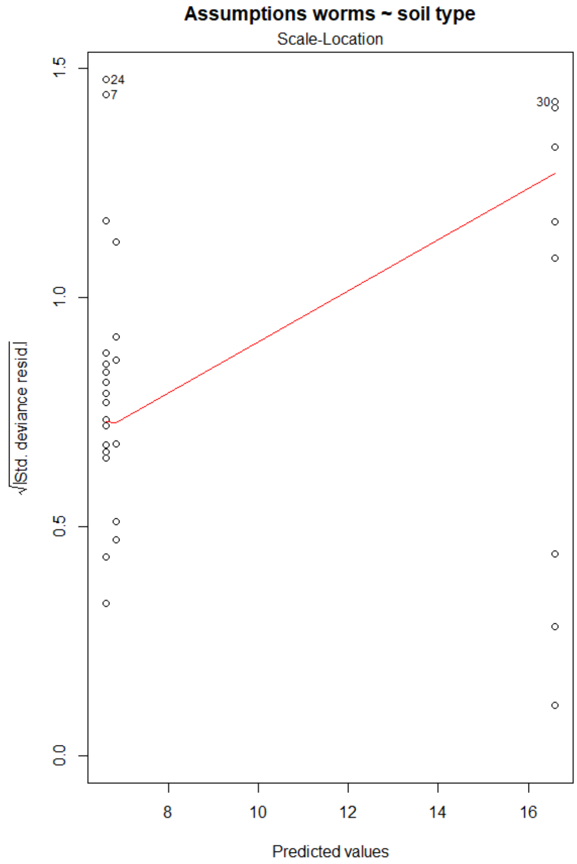


Assumptions Sulphur ~ soil type
Scale-Location
√|Standardized residuals|
Fitted values


Assumptions worms ~ age
Normal Q-Q
Standardized residuals
Theoretical Quantiles
31
30
24


Assumptions worms ~ age
Scale-Location
√|Standardized residuals|
Fitted values
24


Assumptions worms ~ soil type
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
24
30
7


Assumptions worms ~ soil type
Scale-Location
√|Std. deviance resid.|
Predicted values
24
7
30