Ref. Ares(2025)9701823 - 11/11/2025

REFOREST

Organisation: Rheinische Friedrich-Wilhelms-Universitaet Bonn
Department: Institute of Crop Science and Resource Conservation Horticultural Sciences

D4.3

Model Comparison

Date 11.11.2025
Doc. Version 06

Funded by the European Union

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101060635 (REFOREST). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for them.

UK Research and Innovation

UK partners are funded by UK Research and Innovation (UKRI) under UK government's Horizon Europe funding guarantee [grant number 10039700].

Document Control Information

Settings	Value
Deliverable Title	Model Comparison
Work Package Title	Monitoring and Verification
Deliverable number	D4.3
Description	Comparison of the predictive capacity of different model types to capture agroforestry performance
Lead Beneficiary	UBO
Lead Authors	UBO – Andrew Marcil, Prajna Kasargodu Anebagilu
Contributors	UBO – Eike Luedeling, ORC – Colin Tosh
Submitted by	Prajna Kasargodu Anebagilu
Doc. Version (Revision number)	06
Sensitivity (Security):	Low
Date:	11/11/2025

Document Approver(s) and Reviewer(s):

NOTE: All Approvers are required. Records of each approver must be maintained. All Reviewers in the list are considered required unless explicitly listed as Optional.

Name	Role	Action	Date
Martin Lukáč	ReForest Project PI	Approved	11/11/2025

Document history:

The Document Author is authorized to make the following types of changes to the document without requiring that the document be re-approved:

- Editorial, formatting, and spelling
- Clarification

To request a change to this document, contact the Document Author or Owner.
Changes to this document are summarized in the following table in reverse chronological order (latest version first).

Revision	Date	Created by	Short Description of Changes
06	11/11/2025	UBO - Prajna Kasargodu Anebagilu	Final version
05	10/11/2025	CZU – Martin Lukáč	Minor updates
04	28/10/2025	UBO - Prajna Kasargodu Anebagilu	Revised Deliverable to incorporate and address Review Board comments
03	20/06/2025	UBO - Prajna Kasargodu Anebagilu	Final version
02	20/06/2025	CZU – Martin Lukáč	Minor updates
01	17/06/2025	UBO - Andrew Marcil	Initial version

Configuration Management: Document Location

The latest version of this controlled document is stored in https://czuvpraze.sharepoint.com/teams/fld-t-reforest/Sdilene%20dokumenty/Forms/AllItems.aspx

Nature of the deliverable		
R	Report	x
DEC	Websites, patents, filing, etc.	
DEM	Demonstrator	
O	Other	

Dissemination level		
PU	Public	x
CO	Confidential, only for members of the consortium (including the Commission Services)	

Acknowledgements

This report forms part of the deliverables from the REFOREST project which has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101060635. The Community is not responsible for any use that might be made of the content of this publication.

More information on the project can be found at: http://agroreforest.eu/

Additionally, we would like to thank FarmTree B.V. for their permission to include the FarmTree tool in our report, as well as University of Copenhagen and Polish Agroforestry Association for providing and allowing us the use of their field data for the purposes of this report.

Disclaimer

The information presented here has been thoroughly researched and is believed to be accurate and correct. However, the authors cannot be held legally responsible for any errors. There are no warranties, expressed or implied, made with respect to the information provided. The authors will not be liable for any direct, indirect, special, incidental or consequential damages arising out of the use or inability to use the content of this publication or tools presented.

TABLE OF CONTENTS

EXECUTIVE SUMMARY

This report presents a comparison of the outputs generated from two different modelling approaches that have been developed or refined under the ReForest project. In particular, this deliverable provides a comparison between the fully tractable modelling approaches of the FarmTree tools' soil model, developed by FarmTree B.V., and that of an artificial intelligence (AI) machine learning model developed by the Czech University of Life Sciences Prague (CZU) and the Organic Research Centre under this project. This AI model utilises a deep learning convolutional neural network (CNN) developed by CZU using the training dataset from ORC under Task 4.3 (Neural network training, GUI and predictive tool development, and farmer testing). It currently produces predictions for soil organic carbon and plant biodiversity throughout Europe. The FarmTree tool, the second model discussed in this report, is a comprehensive biophysical model for evaluating agroforestry systems and is being adapted to European conditions under the ReForest project. This report compares the two modelling approaches with each other and evaluates them against the field data collected under Work Package 3 (AF system performance) as a form of model validation.

List of Figures

List of Tables

List of Acronyms and Abbreviations

Abbreviation	Definition
AGI	Artificial general intelligence
AI	Artificial intelligence
CANDY	Carbon and nitrogen dynamics
CCB	CANDY Carbon Balance
CFE	Combined food and energy
CNN	Convolutional neural network
DL	Deep learning
DLAI	Deep learning artificial intelligence
FOM	Fresh organic matter
ha	Hectare
kg	Kilogram
LL	Living lab
LUCAS	Laser utilizing communication system
m	Meter
ORC	Organic research centre
SRC	Short rotation coppice
SOC	Soil organic carbon
SOM	Soil organic matter
t	Tonne
UBO	University of Bonn
WP	Work package

1. Introduction

The large-scale advances in scope and utilisation of artificial intelligence (AI) over the past decades have been immense, with advances now occurring exponentially in recent years in terms of functionality as well as application. This has led to an extremely high level of integration into a wide range of applications spanning nearly all industries and markets. This interest has understandably extended towards agricultural management and operational sustainability. From achieving sustainable development goals to enhancing precision agriculture, AI is continually gaining traction as a valuable tool for assessing innovative methods in monitoring and improving agricultural practices.[1,2] This increase in interest led to over 3900 articles published on the role of AI in agricultural management in 2022 alone, and it is very likely that this will continue to increase going forward.[3]

Currently, the focus has been on leveraging AI to streamline and improve agricultural management through smarter, more well-informed and accurate decision-making while simultaneously reducing labour and capital investment.[4] This has the capacity to enable improved decisions pertaining to agricultural practices, which could advance the social, economic and environmental standards across extremely heterogeneous farming conditions.[5] The range of applications currently being investigated using AI in agricultural management spans water management, soil and crop health, weed control, optimising crop harvest timing, predicting future yields, automation, early detection and more. [4,6] Among the various advancements in the use of AI in agriculture, those driven by deep learning (DL) algorithms represent some of the most transformative and promising. DL is a type of machine learning where the AI can automatically construct its own representations and iteratively refine them to create more complex abstractions based on raw data and training data.[7]

One of the major advantages of DL is its ability to automatically learn and create complex representations from raw data, reducing the need for manual engineering and extensive domain expertise. [7] However, this advantage makes higher-level representations and assumptions underlying the DL partially unknown, compared to conventional model building, where the logic and mathematical underpinnings are clearly understood.[8] This is only one of many risks associated with the use of AI systems in real-world applications such as agricultural management. Presently, AI applications in agriculture can be limited due to requirements for access to large data sets, the extreme expense associated with data requirements or time, or restrictions on accuracy or the scope of predictions.[9] Even more concerning is the potential of AI systems to compromise important considerations such as ecosystem health, farmer rights or cultural identity without contextualisation by human decision makers.[6] There are also critical points where AI can negatively affect the quality of life or alter our ability to properly address ethical considerations within agricultural decision-making frameworks.[10] Although speculative, these points highlight the importance of rigorously assessing the strengths and weaknesses of AI within agricultural decision-making prior to deployment into real-world agricultural operations.

This report will assess the feasibility and efficacy of a convolutional neural net (CNN) DLAI to predict the soil organic carbon (SOC) content and biodiversity in agroforestry systems across Europe compared to tractable modelling approaches as developed in the FarmTree tool. The CNNs developed by CZU and ORC through the ReForest project have been trained to predict a one-percentile range of SOC at any given point across Europe, as well as predict the number of plant species found within any

5 km × 5 km area across Europe. These predictions produced by the CNNs are compared to the outputs for SOC and biodiversity produced by the FarmTree tool. The FarmTree tool, under ReForest, is being updated to simulate agroforestry systems in Europe based on the data collected from the different living labs of the project. Additionally, we evaluate how these two models' predictions compare to the field data measurements, collected under the purview of the ReForest project in work package 3.

2. Methodology

2.1 Background

At the time of this assessment, only the FarmTree tool had been used within the ReForest project to analyse SOC and biodiversity through *Task 3.6: Calibration and validation of AF models to simulate productivity and economic returns*. As such, this report includes an analysis of outputs for SOC and biodiversity between the FarmTree tool and the CNN developed by the CZU and ORC under *Task 4.3: Neural network training, GUI and predictive tool development, and farmer testing*. This report identifies where meaningful comparisons can be made between the prediction metrics of the two models, and where such comparisons are either not viable or offer limited value. Based on these outcomes, we identify the individual functionalities of these two types of models and the contexts in which they can provide valuable predictive support that can be leveraged by farmers, policymakers, researchers, or other stakeholders. Both models are briefly described below to provide context. A full description of the creation and use of these models, detailed structural diagrams, and details of further refinements can be found in Appendix 2: Report on Big Data Modelling Opportunities in Agroforestry. A comprehensive description of the FarmTree tool and the methodology underlying the production of performance indicators can be found at https://www.farmtree.earth/.

Convolutional Neural Networks

The Convolutional Neural Networks developed under the ReForest project are an example of a big data model development which works on imagery datasets of 1TB in size or larger. These have been used to develop two separate predictive models, which have the capability to predict SOC and biodiversity across Europe.

The V1 biodiversity and soil carbon CNNs were built using data-driven workflows that pair Sentinel-2 multispectral imagery with field measurements. In each case, image tiles were generated around field sample points using Google Earth Engine, filtered for clouds, atmospherically corrected, and downloaded for further processing.

Technical specifications are described below:

Carbon V1 CNNs [https://soilcarbonestimator.fld.czu.cz/]

- Patch size: 500 m × 500 m Sentinel-2 tiles.

- Training data: Two sets of patches—18,000 points from the pan-European LUCAS 2018 topsoil survey (covering natural and human-modified environments) and 20,000 soil sample points from Czech agricultural fields (data set curated by Dr Michaela Smatanova, Institute for Supervising and Testing in Agriculture, Czechia) - produced the "LUCAS" and "Czech" versions, respectively.

- Network design: Layers of convolutional filters scan each tile to pick up spectral and textural patterns, which are then summarised and fed through dense layers to assign one of several soil carbon classes.

Biodiversity V1 CNN [https://biodiversityestimator.fld.czu.cz/]

- Patch size: 5 km × 5 km Sentinel-2 mosaics.

- Sampling extent: About 22,000 patches centred on GBIF-recorded plots in Spain, Sweden, Switzerland and the Netherlands.

- Network design: A series of convolutional blocks learns from the full 13-band imagery, with its output passed to dense layers that estimate plant species richness.

By relying entirely on end-to-end convolutional learning, the V1 CNNs distil complex spectral–environmental signals into networks of learned weights, delivering rapid, data-driven predictions while offering little transparency as to which image features drive each outcome. Although the CNNs can generalise to new, similar images, they do not expose the causal pathways behind their predictions or support direct simulation of hypothetical changes. In short, the V1 CNNs developed under the ReForest project trade interpretability for streamlined pattern recognition.

FarmTree

The FarmTree Tool is a software model integrated into a user-friendly online interface that allows users to design their own agroforestry systems and view the resulting effects on over 100 performance indicators, ranging from environmental indicators to financial metrics, climate/carbon, productivity, and more. The model relies on a variety of data metrics and databases to inform interconnected sub-models, resulting in various performance indicators (Figure 1).

The soil model is based on the Carbon and Nitrogen Dynamics (CANDY) and CANDY Carbon Balance (CCB) models.[11,12] From this, SOC is calculated based on the dynamics of soil organic matter (SOM) and fresh organic matter (FOM) deposition and decomposition. These values themselves are derived from the conditions of leaf and litter, mulch and fertiliser inputs. The general assumption for the distribution of SOC as it leaches and distributes through the soil profile is that the topsoil (assumed to be the upper 30cm of the soil profile) contains the majority of the nutrients within the 2m soil depth.[11] The general assumption for the distribution of SOC as it leaches and distributes through the soil profile is that the topsoil (assumed as the upper 30cm of the soil profile) contains 92% of the distribution of nutrients, whereby considering an effective total subsoil depth of 2m would equate to the topsoil containing 71.4% of the total SOC in the system.

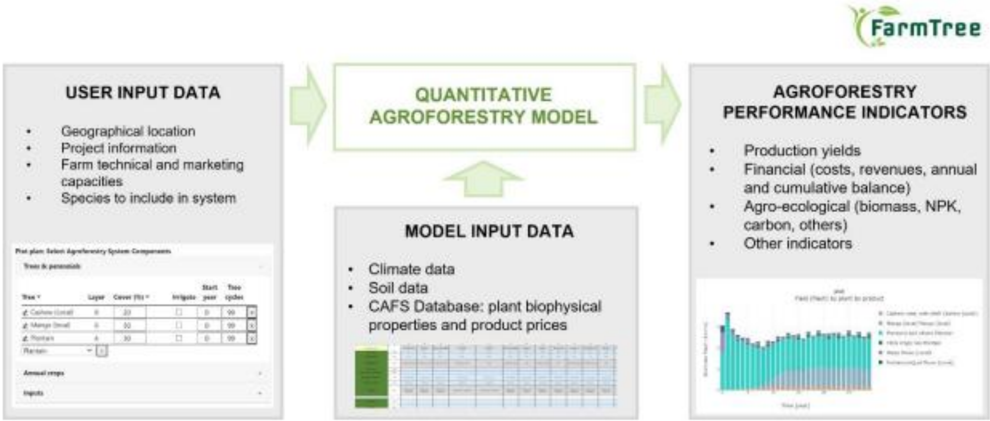


Figure 1: Overview of the FarmTree models' methodology and workflows.

For the biodiversity measure, the FarmTree Tool utilises the Shannon or Shannon-Weaver Index, a widely used metric of biodiversity that accounts for species richness and abundance (evenness) to provide a measure of biodiversity (Shannon, 1948).[13] This relative measure of biodiversity is calculated with species richness and evenness using the following formula:

$$H' = -\sum_{i=1}^{s} pi \ln(pi)$$

S: Species richness
p_i: Proportion of total sample represented by species *i.*

The FarmTree Tool calculates the Shannon Index scores by determining the plant richness and evenness of the planted species within the agroforestry system. These allow users to see how different planted arrangements affect species richness and evenness of the planted communities in the agroforestry design.

2.2 Model Comparison – Soil Organic Carbon

The Czech and LUCAS CNN predictive tool for carbon and biodiversity assessment outputs for SOC consists of a predicted category of SOC that spans a single percentage (0-1%, 1-2%, etc.) at any given set of coordinates. Farm boundaries were extracted from the FarmTree tool, and the extent of farm areas was assessed in a 5 m grid. This resulted in large datasets of predicted SOC values, which effectively cover the entire agroforestry system with point predictions of SOC.

In contrast to the CNN outputs, the FarmTree tool scenarios produce an estimation of the average SOC found throughout the entire agroforestry system, calculated in terms of tonnes per hectare (t/ha), and provide an estimated flux of this SOC concentration in a time series throughout the scenario's duration. To ensure that the correct year of simulation was chosen, the start years for tree species were checked against the year of establishment of the agroforestry system to ensure that the year number within the scenario corresponded to the 2022 imagery used by the CNN to train itself to predict SOC concentrations. The appropriate timestep year within the FarmTree tool was then used within the FarmTree tool soil model to determine the estimated SOC content in t/ha, which was then converted into an SOC percentage using the following calculation:

$$SOC(\%) = \frac{SOC(t\ /\ h_a) \times TC}{(10{,}000\ m^2 /\ h_a) \times BD \times TD}$$

TC: Percent of SOC found in topsoil (71.4 %)
BD: Bulk density (kg/dm^3) or (t/m^3)
TD: Topsoil depth (0.3 m)

The values for topsoil depth and topsoil carbon content reflect those used in the FarmTree tool model predictions (FarmTree, pers. comm.). The FarmTree tool also estimates the bulk density for the soils found in the agroforestry system based on the plot settings and coordinates of the system. Below is an example calculation for the German LL nut system, which, having been established in 2020, corresponds to the second year timestep in the FarmTree prediction tool, aligning with the 2022 imagery used in CNN predictions. At timestep 2, the FarmTree tool soil model estimated an SOC content of 56.1 t/ha:

$$SOC(\%) = (56.1t/ha)(71.4\%)/(10000m2/ha)(1.2t/m3)(0.3m) = 1.11\%$$

2.3 Model Comparison – Biodiversity

Numerous attempts were made to find a way to compare the outputs of biodiversity measures between the predictive tool for carbon and biodiversity assessment and the FarmTree tool. All of these proved unsuccessful, as it was determined that the outputs did not share any commonality which would allow for any type of comparison. The predictive tool for carbon and biodiversity assessment produces an estimate of the number of plant species representing the full species richness (planted species, native species, invasive species, volunteer species, etc.) covering an area of 5 km x 5 km centred on the chosen coordinates. The FarmTree tool's biodiversity measure is calculated based solely on planted species. Thus, no solution was found to overcome the difference between the spatial scales (5 km x 5 km compared to the precise boundaries of agroforestry systems) and the species comprising the estimate (all plant species present versus planted species only).

2.4 Living Lab Site Selection

As the living lab (LL) network developed under ReForest is a central piece of the project's scope, it was determined that the farms within these LLs would be the most suitable for evaluating the models. To ensure consistency and completeness in the analysis, the assessment focused on farms within the LL network that had completed scenarios using the FarmTree tool as a baseline for selection. The second metric used to filter LL farms was the availability of field measurements under WP3, which included laboratory-measured SOC data from the field samples collected at the LL farms. Based on these criteria, the Danish LL at the University of Copenhagen's experimental plot at Taastrup farm and the original German LL farm were chosen as suitable candidate farms. The Czech Republic LL, Daniel Pitek farm, although lacking field data from WP3 for validation of model predictions, was also chosen as an LL farm of interest due to the Czech dataset used to train one of the two CNN models. It was decided that analysing a farm from the Czech Republic would be a valuable addition to this country-specific dataset, enabling the establishment of accuracy differences between the Czech sites and those in the rest of Europe. Brief descriptions of each of the three LL farms within our analysis are given below:

Czech Republic Living Lab - Daniel Pitek Farm

The Daniel Pitek farm is a 599.06 ha grazing and orchard operation with the integration of numerous agroforestry parcels throughout the farm complex. Agroforestry systems consist of the careful integration of livestock into orchards, as well as trees into existing pastures. The tree species used in these systems include ash, beech, linden, birch species, maple species, alder species, wild pear, bird cherry, and apple. Livestock integration typically begins with sheep grazing, followed by cow grazing once the system has reached sufficient maturity.

Denmark Living Lab - Taastrup Farm

The Taastrup farm is an experimental farm associated with the Department of Plant and Environmental Sciences at the University of Copenhagen. The system is a 10.1 ha combined food and energy (CFE) system established in 1995, which combines short rotation coppice (SRC) with arable crops, including barley and wheat, as well as clover/ryegrass fodder. The woody SRC strips consist of four woody belts, 11 m in width, comprising willow species, hazel, and alder. The woody strips have been planted at varying widths of 50 m, 100 m and 200 m to understand spatial effects on crop and fodder growth.

German Living Lab Farm

The former German LL farm incorporates various elements, including outdoor gardens, a tree nursery, greenhouses and two distinct agroforestry systems. The first system, planted in 2020, was a 7.53 ha alley cropping system featuring a variety of nut-bearing tree species, including walnut, chestnut, pecan, almond, hickory, and hazelnut. The second system, planted in 2022, was a 10-hectare alley cropping system featuring a variety of fruit-bearing species, including pear, quince, apple, common medlar, apricot, peach, sweet cherry, and persimmon.

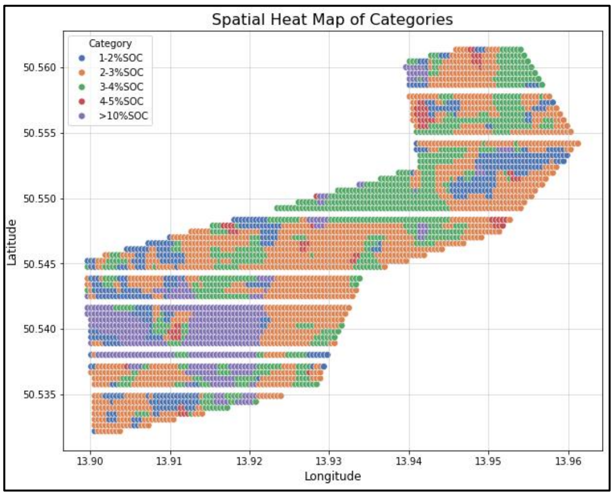
3. Results

3.1 Czech Republic Living Lab - Daniel Pitek Farm

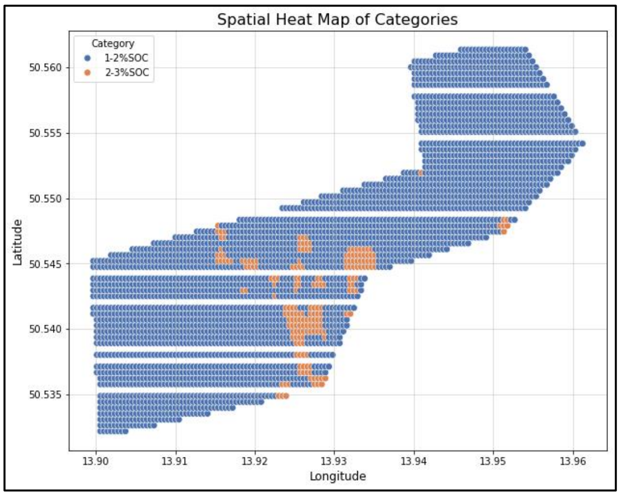
Based on the LUCAS predictive tool for carbon and biodiversity assessment, the estimated SOC on the Daniel Pitek farm ranged from 1-2% to 10-11%, where the majority of the estimations predict an SOC content between 3-5% (Figure 2A).

The most common SOC category predicted by the LUCAS predictive tool for carbon and biodiversity assessment was a soil content of 3-4% SOC (Figure 2A). In contrast, the Czech CNN predicted a SOC content of 1-3%, with the vast majority of estimates ranging from 1 to 2% (Figure 2B). These results show the Czech CNN predicted a much more conservative estimate of SOC compared to the model trained using the LUCAS dataset. The Czech trained CNN also showed a strong preference towards the lowest range class of 1-2 %, while the LUCAS CNN was much more dynamic in its predictions, predicting five different SOC categories compared the the Czech CNNs two, as well as predicting over 13 % of all point values within the Daniel Pitek farm to have an SOC content of 10 % (Figure 2A).

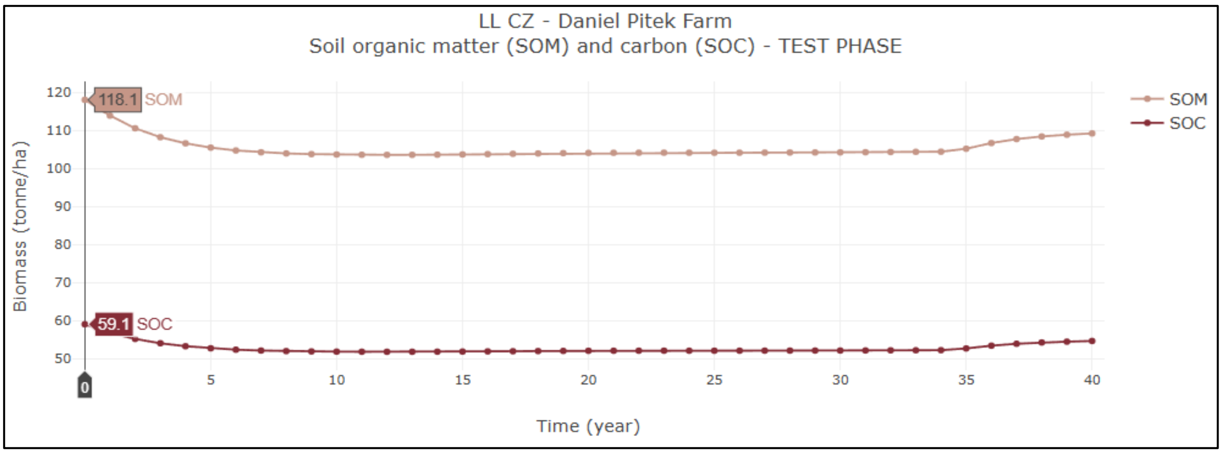
When considering the FarmTree tool soil model, the soil model estimated a total SOC of 59.1 t/ha or 1.17 % for year zero of the scenario, which equates to the year 2022 (Figure 2C). This predictive value more closely aligns with the predictions made by the Czech CNN, which predicted that the majority of the farm systems would contain an SOC content between 1-2%. Due to the range nature of the CNN predictions, it is unclear how the point predictions in the Czech CNN model, between 2-3%, would affect the overall agreement between models (Figure 3B).



A



B



C

*Figure 2: SOC Predictions from the two Convolutional Neural Network models and the FarmTree tool soil model for the Czech living lab Daniel Pitek farm. **A**: Results from the CNN trained from the LUCAS dataset **B**: Results from the CNN trained from the Czech dataset. **C:** Results from the FarmTree soil model.*

Conversely, the LUCAS CNN predicted that the Pitek farm contained a higher SOC content, with the vast majority of the points predicting values above 2 % or 3 % (Figure 2A). This makes the LUCAS predictions extensively different from those derived from the other two models (Figure 2). As no soil sampling was completed for this LL site, it was not possible to validate these model predictions with field-derived measurements.

3.2 Danish Living Lab – Taastrup Farm

Similar to the results seen in the Czech Republic LL predictions, the LUCAS CNN predicted higher SOC content within the Taastrup farm predictions than the private Czech dataset; however, these estimates were significantly lower than those predicted in the Czech Republic LL (Figure 3).

The LUCAS CNN predicts that the SOC across the majority of the Danish LL experimental site ranges from 1-2%, with two regions containing higher SOC content, between 2-3% (Figure 3A). This matches closely with the majority of the SOC predictions made using the Czech CNN, which predicts the whole experimental site to contain an SOC content between 1-2 % (Figure 3B).

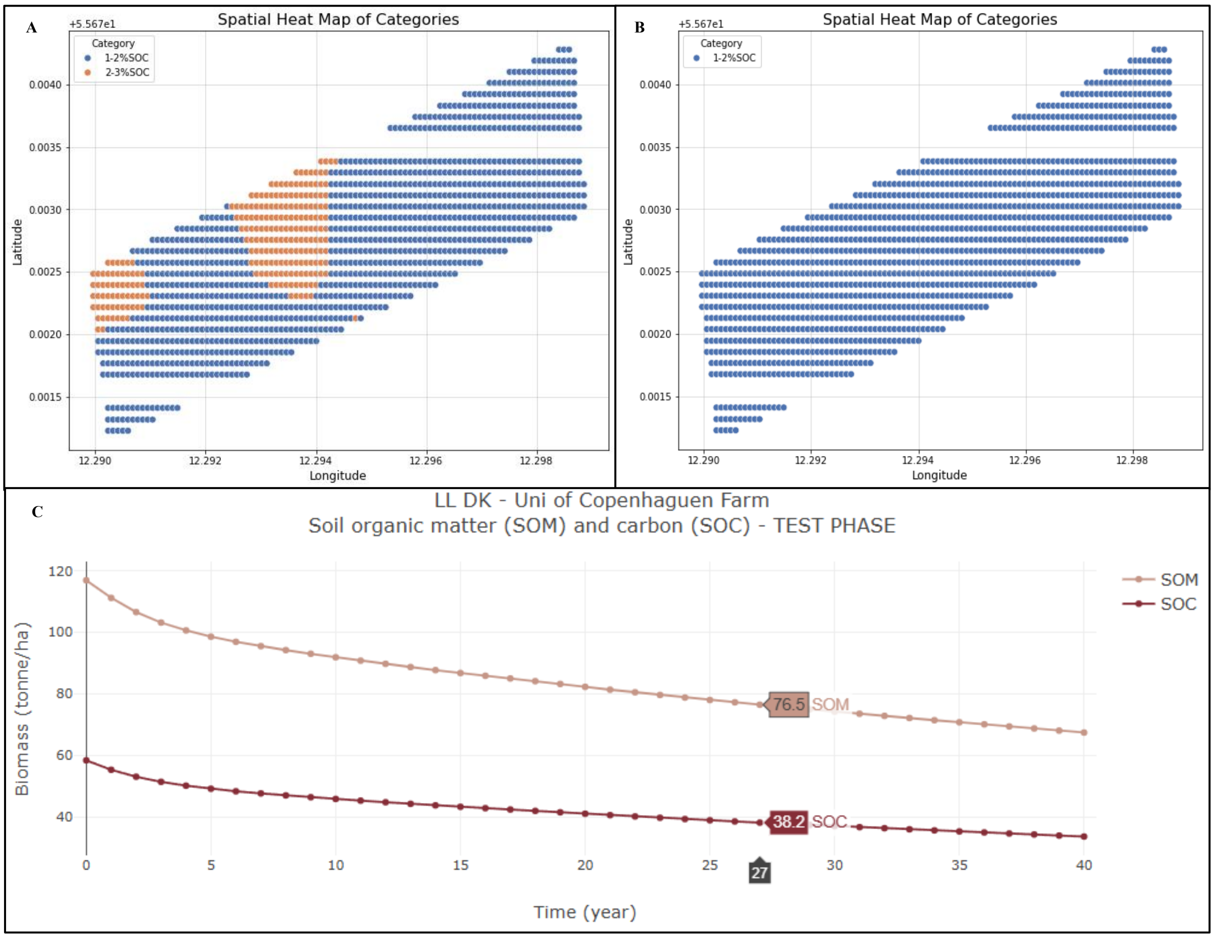


*Figure 3: SOC Predictions from the two Convolutional Neural Network models and the FarmTree tool soil model for the Danish living lab experimental plot, Taastrup farm. **A**: Results from the CNN trained from the LUCAS dataset. B: Results from the CNN trained on the Czech dataset. **C:** Results from the FarmTree soil model.*

With an establishment year of 1995, the 2022 imagery used to inform the CNN model equates to the 27th year from the establishment date within the FarmTree scenario. At this timestep, the FarmTree tool estimates that the SOC content of the farm was 38.7 t/ha, which corresponds to an average SOC content of 0.77% across the Taastrup farm (Figure 3C; Table 1). As the CNN models do not create predictions below 1 %, both the CNN models estimate a higher SOC than the FarmTree model. With the Czech CNN model predicting lower overall SOC content throughout the site, once again, the Czech CNN model is in higher agreement with the predictions made by the FarmTree tool, although these are higher than the estimated 0.77 % SOC predicted by the FarmTree tool's soil model.

Considering the eleven laboratory-tested soil samples from this LL site, SOC ranged from 1.33 % to 2.32 % with an average of 1.85 %. These field values are similar to estimates provided from both CNN models (Table 1). When we look at these CNN predictions at each sampling location, we then see that the LUCAS CNN model correctly predicted the SOC range for these soil points for four of the eleven soil locations, or a 36 % accuracy in predicting the SOC of the sampling sites (Table 1). This was lower than the predictive success of the Czech CNN, which was successful in predicting the SOC range in six of the eleven soils points, or 55 % of the sampling sites being correctly predicted (Table 1).

Farm System	Field Sample Number	Latitude (decimal °)	Longitude (decimal °)	Laboratory SOC (%)	LUCAS CNN SOC (%)	Czech CNN SOC (%)	FarmTree SOC (%)
Danish LL - Taastrup Farm	1	55.6728933	12.2929613	1.334	2-3	1-2	0.77
	2	55.6724742	12.2930594	1.392	2-3	1-2	0.77
	3	55.6720907	12.2931485	1.798	1-2	1-2	0.77
	4	55.6728042	12.2925867	1.508	1-2	1-2	0.77
	5	55.6724073	12.2926848	2.03	1-2	1-2	0.77
	6	55.6720193	12.2927695	2.262	1-2	1-2	0.77
	7	55.6726302	12.291851	1.798	1-2	1-2	0.77
	8	55.6722155	12.2919178	2.03	1-2	1-2	0.77
	9	55.6718098	12.2920159	2.32	1-2	1-2	0.77
	10	55.6729959	12.2933403	2.03	2-3	1-2	0.77
	11	55.6725946	12.2934384	1.885	2-3	1-2	0.77
German LL Farm	1	49.7130239	7.7676158	2.74	1-2	1-2	1.17
	2	49.7131487	7.7676381	2.69	1-2	1-2	1.17
	3	49.713278	7.76768715	2.74	1-2	1-2	1.17
	4	49.7134296	7.76775849	2.53	1-2	1-2	1.17
	5	49.7128455	7.76741068	1.56	1-2	1-2	1.17
	6	49.7129926	7.7674419	1.64	1-2	1-2	1.17
	7	49.7131532	7.76749095	1.62	1-2	1-2	1.17
	8	49.7132914	7.76753554	1.55	1-2	1-2	1.17
	9	49.7093273	7.76181897	2.31	1-2	1-2	1.11
	10	49.7093852	7.76189032	1.8	1-2	1-2	1.11
	11	49.7094432	7.76196612	2.12	1-2	1-2	1.11
	12	49.7095012	7.76205976	2.01	1-2	1-2	1.11
	13	49.7092158	7.76185019	1.91	1-2	1-2	1.11
	14	49.7092827	7.76194383	2.16	1-2	1-2	1.11
	15	49.7094432	7.76218462	1.45	1-2	1-2	1.11

Table 1: Results of the laboratory Soil Organic Carbon (SOC) from the Danish and German LL farms and the predictions of SOC at these points from the two CNN models and FarmTree tool.

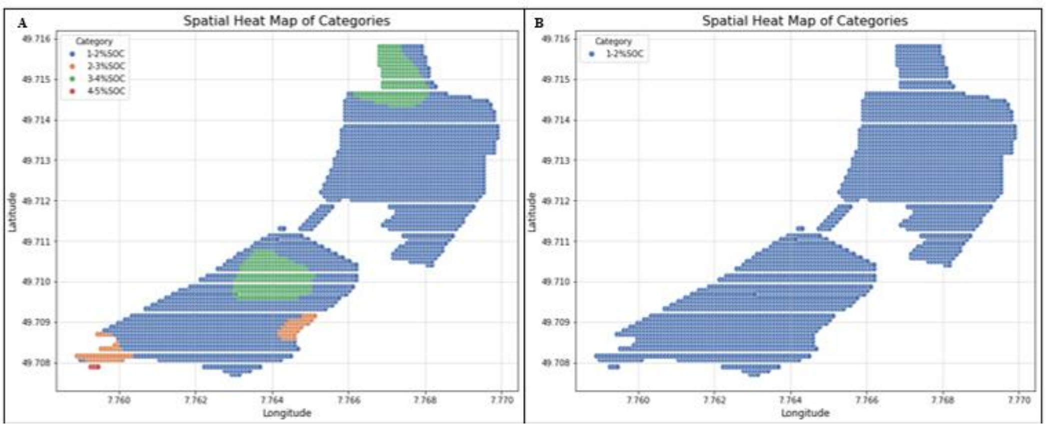
Despite the Czech CNN showing a higher success rate in predicting the soil samples' SOC, the LUCAS CNN did make predictions of SOC higher than 2 % which is in line with the validated laboratory analyses, while the Czech CNN did not predict any points within the Taastrup farm area to contain an SOC above 2 % (Table 1). When comparing the overall laboratory results from the soil sampling of Taastrup farm, the FarmTree tool estimates were found to be lower than all sampled locations (1.33 % minimum) with its predicted SOC of 0.77 % (Table 1).

3.3 German Living Lab Farm

When comparing the two CNN models, the Czech CNN once again predicted that the entirety of the LL farm site would contain an SOC between 1-2%, while the LUCAS CNN predicted certain regions of the farm to contain higher SOC levels between 2-5% (Figure 4). The LUCAS CNN is in agreement with the Czech CNN for the majority of the farm area, estimating an SOC content of 1-2 %, with two regions containing 2-3 % and 3-4 % and three points in the southwest corner of the farm site containing the highest SOC content of 4-5 %. (Figure 4).

For the German LL, two FarmTree scenarios were created for the nut and fruit systems separately. With the establishment of the fruit system in 2022, this equates to timestep zero of the FarmTree tool scenario and an estimated SOC content of 58.8 t/ha, or 1.17 % (Figure 4C; Table 1). The nut system, established in 2020, corresponds to timestep 2 in the scenario, leading to an estimated SOC of 56.1 t/ha or 1.11 % (Figure 4D; Table 1). Due to the range nature of the CNN predictions, it is difficult to determine which of the two models more closely relates to the SOC percentages predicted by the FarmTree model, however, the Czech CNN estimates consistently between 1-2 % would appear to be more in line with the 1.11 % SOC as predicted by the FarmTree tool (Figure 4).

The laboratory analysis of the soil samples taken from the German LL ranged from 1.55% to 2.74%, with an average SOC of 2.13% within the fruit system. In contrast, the nut system contained SOC ranging from 1.45% to 2.31%, with an average of 1.89% (Table 1). Considering the estimates made by the two CNN models and the FarmTree tool, all three models appear to show estimates that are not extremely far from those determined through laboratory analysis (Table 1). Considering the two CNN models' predictions at the precise locations of the sampling sites, we see that both models predicted that all sampling points to contain an SOC content between 1-2 %, which was in line with the laboratory results in 7 of the 15 samples, or 47 % of the sampling locations. Although the LUCAS CNN model did not predict SOC contents above 2 % at the sampling locations, it did predict that certain areas of the German LL would contain regions where SOC exceeded 2 % which is in line with the field measurements (Figure 4A; Table 1).



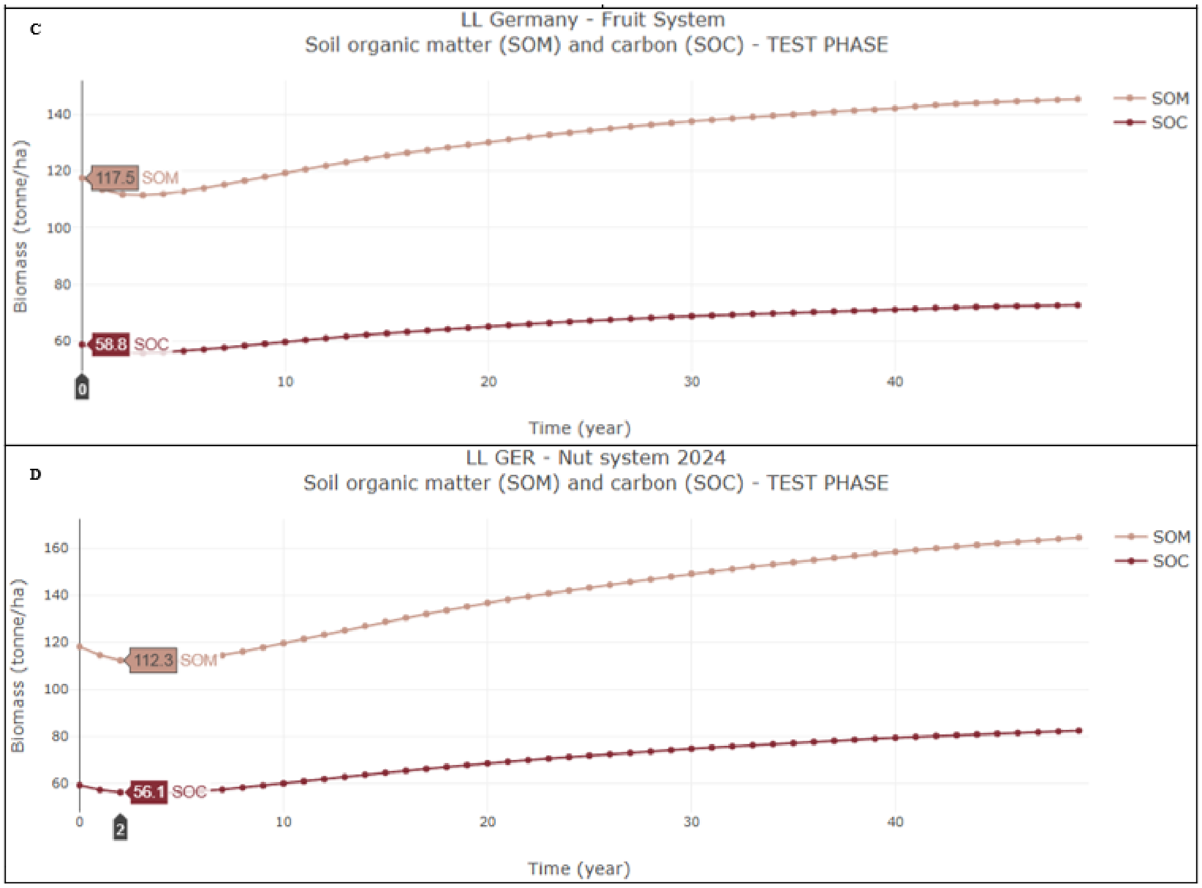


Figure 4: SOC Predictions from the two Convolutional Neural Network models and the FarmTree tool soil model for the former German living lab farm. ***A****: Results from the CNN trained on the LUCAS dataset. B: Results from the CNN trained on the Czech dataset.* ***C:*** *Results from the FarmTree soil model for the German LL fruit system.* ***D:*** *Results from the FarmTree soil model for the German LL nut system.*

4. Concluding Summary

For the ReForest project, where CNN models are being developed and the FarmTree tool is being improved by integrating data from temperate agroforestry systems through the Living Labs, these diverse approaches create valuable opportunities to develop tools tailored to the needs of different users and decision-makers. More importantly, this comparison showcases the range of methodologies for estimating SOC and biodiversity across scales, laying the foundation for future model integration and harmonisation. By demonstrating how different modelling frameworks can complement or compete with one another, the work promotes a more flexible and adaptive approach to assessing agroforestry's ecosystem services. This not only enhances the scientific understanding of system performance but also supports the creation of decision-support tools that are responsive to both research and practical management contexts.

However, when viewed in a broader context, this report highlights the complementary strengths of spatial and temporal modelling approaches for evaluating SOC and biodiversity in agroforestry systems. The CNN models provide rapid, spatially explicit estimates of SOC across large areas, making them particularly useful for policymakers and researchers interested in regional or landscape-level monitoring. In contrast, the FarmTree tool provides detailed time-series analyses at the farm scale, enabling advisors to assess the effects of management decisions on SOC dynamics and biodiversity over time. While the eventual implementation of the CNN model lends itself to a simplified GUI more suitable for farmers, the detail captured by the FarmTree models makes it more suitable for use by advisors and people supporting farmers by providing information. By contrasting these tools, the analysis illustrates how model choice should depend on the stakeholder's objectives, data availability, and the desired scale of application.

Across all three LL farms reviewed in this report, the CNN models and the FarmTree tool's soil model were in relative agreement regarding the SOC content of the three different LL systems. All models predicted that the Czech Republic LL would contain the highest SOC, the German LL was estimated to contain intermediate levels of SOC, while the Danish LL system was predicted to contain the lowest SOC. This is supported by the laboratory results from the two sites, where the German LL contained a higher average SOC of 2.13% and 1.89%, compared to the average SOC content of 1.85% in the Danish LL system (Table 1). Across all three LL sites, the Czech CNN model predicted much more conservative SOC values than those of the LUCAS CNN and was in closer agreement with the predictions made by the FarmTree model. The LUCAS model was the only CNN model that consistently predicted SOC values across sites that exceeded 2%, whereas the Czech CNN model only predicted an SOC outside of the 1-2% range for the Czech LL farm (Figure 2-4). This indicates that although the Czech CNN performed better in predicting the sampling points for the Danish LL, both the Danish and German LLs contained soil samples with an SOC content above 2%, which was only predicted by the LUCAS model, albeit not at the sampling locations themselves (Table 1). This appears to show that the LUCAS CNN model might be better suited to incorporate imagery elements into a more dynamic set of estimations, which might prove more accurate over the course of further validation.

Although there were discrepancies between the predictions made by the CNN models and the FarmTree tools soil model when compared to the laboratory measured SOC at the German and Danish LL sites, the limited number of field samples taken does constrain our ability to predict the whole heterogeneity of the SOC across these two farms (Table 1). Further sampling of these farms may provide further insight into the efficacy of these models in predicting the overall SOC content of these sites and would be useful for future research and for further validation and evaluation of the CNN and FarmTree models.

When evaluating the CNN models and the FarmTree soil model, it becomes quite apparent that these two models have been developed to produce different predictions, which do not fully align. The most notable difference between the CNN modelling and that of the FarmTree is the spatial nature of the CNN predictions versus the time series estimations provided by the FarmTree tool. The other major difference between the two models is the categorical estimations provided by the CNN models, where SOC is predicted within 1% of the actual SOC, which is a limitation in terms of spatial accuracy, as it cannot predict this metric at any single point across Europe. The FarmTree tool's soil model, on the other hand, has no capabilities to pinpoint SOC at any location, but uses rigorous modelling to predict a precise SOC content at the farm level, in addition to these fluxes over time. Due to the CNN models being trained on 2022 imagery, a more in-depth analysis of how these models compare over time was not possible at the time of writing. Still, future development of the CNN with additional years of imagery may allow for further analysis. This, amongst the other differences in model predictions, did not allow for a robust review of the various strengths and weaknesses of the models in comparison to one another.

The different strengths and weaknesses associated with the two predictive models underscore the need to frame the use of the models as extremely context-dependent, and one must consider both the stakeholder or stakeholder group and the anticipated outcomes and requirements. The spatial nature of the CNN predictions for SOC is a powerful tool for understanding soil heterogeneity across a local area, such as a farm site, but could also be leveraged to explore SOC variability at larger scales, such as for assessment at landscape or regional levels. Alternatively, the spatial variability might not be the primary goal of the stakeholder's assessment, where instead the ability to visualise SOC dynamics over time in a predetermined area is more effectively addressed by the FarmTree tool's soil model. One can imagine that a farmer looking to better understand the outcomes of agroforestry on his farm would not require a spatial tool to pinpoint SOC predictions but instead would be able to leverage a time series of how the SOC content shifts based on his decisions. On the other hand, a policymaker or research organisation might find the ability to access a SOC measurement at any point in Europe to be crucial to reaching their respective goals. The CNN models also provide a very quick result, where simply inputting coordinates allows for an estimate, rather than requiring the input of a scenario. However, in cases where a precise measurement of SOC is required, the FarmTree tool provides the exact value of anticipated SOC for a predetermined system, compared to the ranges provided by the CNN models. In this respect, the CNN produced under WP4 does not provide improved predictions of SOC in agroforestry systems but instead provides a novel and useful output which can be used to support agroforestry decision making in different but potentially complementary ways to the FarmTree tools soil model for predicting SOC.

As discussed above, regarding the limitations in comparing the SOC predictions between the two modelling approaches, these limitations become even more apparent due to the inability to create a meaningful comparison between the models for the outputs pertaining to biodiversity. Once again, the different models are designed to predict and inform very different parameters, and each provides its own valuable insights. The current functionality of the CNN biodiversity model offers predictive plant species richness at a 5 km x 5 km scale, which would be extremely useful for landscape or regional assessments and management. Although estimations at a finer scale were hoped for, the lack of a more robust dataset across Europe made the 5 km x 5 km scale the most accurate, allowing the tool to function across the entirety of the European continent (Organic Research Centre, pers. comm.). On the other hand, the biodiversity measure provided by FarmTree appears more suited to understanding the local effects at the farm level, particularly the direct impact of design choices on the richness and evenness of the planted species communities within the agroforestry system. As these models continue to progress and as more models are assessed under the ReForest project, it is possible that more meaningful comparisons and a better understanding of the model's complementarity in providing predictions for stakeholders will be of great interest for future research.

Although a direct comparison of biodiversity outcomes between the CNN and FarmTree models was not feasible, primarily because of differences in data structure, such as total species richness versus planted species richness, several alternative approaches could enable more meaningful comparisons in the future. One promising direction would be to apply widely known biodiversity indices, such as the Shannon or Simpson diversity indices, which integrate both species richness and evenness into a single, comparable metric that can be applied across spatial scales. Another valuable approach could involve using functional diversity metrics to group species by shared ecological benefits. This would make it possible to capture biodiversity benefits rather than composition alone.

To enhance comparability between models, it would also be beneficial to harmonise data collection protocols or establish shared reference sites and plot-level datasets for calibration and validation. Furthermore, developing scaling relationships between field-level diversity, as represented in FarmTree, and landscape-level predictions, as modelled by the CNN approach, could facilitate integrated assessments that connect local management effects with regional biodiversity outcomes. Together, these strategies would enable a more robust and scientifically consistent comparison of biodiversity findings across modelling frameworks, while maintaining their relevance for both research and practical decision-making.

While the comparison between the two modelling approaches remains constrained by differences in scale, data, and methodological scope, it still offers valuable insights into the diversity of assessment strategies available for agroforestry systems within and beyond the ReForest project. The coexistence of these models enhances the availability of agroforestry tools by offering complementary perspectives: one suited for regional or landscape-level analyses, and the other for farm-scale design and management decisions.

As a team analysing these tools, we recognise that their usefulness depends on the specific objectives and contexts of the users. Therefore, we encourage both model developers to incorporate more user-friendly indicators that allow farmers, advisors, and land managers to easily communicate their results to institutions and stakeholders, as well as for their own sustainability reporting. Aligning tool development more closely with end-user information needs will ensure that these models not only advance scientific understanding but also provide practical, decision-oriented support for those implementing and promoting agroforestry systems.

At the time of writing, the soil model used by the FarmTree tool is still under development. The FarmTree tool models are all iterative and are constantly being updated. With dozens of output variables being managed and refined, the soil model, including the SOC predictions used in this report, was still being finalised (Figures 2C, 3C, 4C, 4D) (FarmTree, pers. comm.). Due to the deadline of this report, the test phase data was used. It is recommended that an updated assessment be made once the soil model and SOC predictions of the FarmTree tool are updated. The updated soil model may better facilitate comparisons with the CNN models using laboratory-measured samples.

Appendix 1: References and Related Documents

ID	Reference or Related Document	Source or Link/Location
1	Ayoub Shaikh, T., Rasool, T., & Rasheed Lone, F. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. Computers and Electronics in Agriculture, 198, 107119.	https://doi.org/10.1016/j.compag.2022.107119
2	Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications, 11(1), 233.	https://doi.org/10.1038/s41467-019-14108-y
3	Sood, A., Bhardwaj, A. K., & Sharma, R. K. (2022). Towards sustainable agriculture: key determinants of adopting artificial intelligence in agriculture. Journal of Decision Systems, 33(4), 833–877.	https://doi.org/10.1080/12460125.2022.2154419
4	Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in the Agriculture Sector. Advanced Agrochem, 2(1), 15–30.	https://doi.org/10.1016/j.aac.2022.10.001
5	Kisliuk, B., Krause, J. C., Meemken, H., Saborío Morales, J. C., Müller, H., & Hertzberg, J. (2023). AI in Current and Future Agriculture: An Introductory Overview. KI - Künstliche Intelligenz, 37(2–4), 117–132.	https://doi.org/10.1007/s13218-023-00826-5
6	Tzachor, A., Devare, M., King, B., Avin, S., & Ó hÉigeartaigh, S. (2022). Responsible artificial intelligence in agriculture requires systemic understanding of risks and externalities. Nature Machine Intelligence, 4(2), 104–109.	https://doi.org/10.1038/s42256-022-00440-4
7	LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.	https://doi.org/10.1038/nature14539
8	Dablain, D., Jacobson, K. N., Bellinger, C., Roberts, M., & Chawla, N. V. (2024). Understanding CNN fragility when learning with imbalanced data. Machine Learning, 113(7), 4785–4810.	https://doi.org/10.1007/s10994-023-06326-9
9	Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. Engineering, Technology & Applied Science Research, 9(4).	https://doi.org/10.48084/etasr.2756
10	Ryan, M. (2023). The social and ethical impacts of artificial intelligence in agriculture: Mapping the agricultural AI literature. AI & SOCIETY, 38(6), 2473–2485.	https://doi.org/10.1007/s00146-021-01377-9

11	Franko, U., Kolbe, H., Thiel, E., & Ließ, E. (2011). Multi-site validation of a soil organic matter model for arable fields based on generally available input data. Geoderma, 166(1), 119-134.	https://doi.org/10.1016/j.geoderma.2011.07.019
12	Franko, U., Witing, F., Thiel, E., Ließ, E., Diel, J., & Gasser, A. (2017). CCB Manual.	https://d1wqtxts1xzle7.cloudfront.net/121103317/226120_CCB_Manual_19p-libre.pdf?1738249374=&response-content-disposition=inline%3B+filename%3DCCB_Manual_Version_20_19_1_14.pdf&Expires=1748945355&Signature=IESNLlIRpXLOu8K1kQaZfoR3uSGQxTCTe7hOKhIvYTirvpy7IxXdMg0XpPmSRKowMdXffqdL~HDWFEwGg5GRAXS4tJDq9v~t2yo4iiueL6sQblhUKbBVxIMBgh2sygUaW6Y~ZNTpk9L8VIFPJAhsztLO-fL0iEXvuBHVN9nzWzADegZ3lTWfYy0X6jGCBQ72vet7XLL8Wj~FupHIJbd7I1jTx7kValgM12sH3CBKbnvxfwZrAB0rzJLQ5P10yEvuC8vDRqQhTWne3i4vlzRTm2XqQzlDTQ-d7EQxJwaqL8lo5sNFZv-p7FfRjqE6rv1xzaczAGxs0iKjfVDsFeutog__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA
13	Shannon, C.E. (1948). A mathematical theory of communication. Bell System Technical Journal 27:379–423	DOI 10.1002/j.1538-7305.1948.tb01338.x.

APPENDIX 2: M19: REPORT ON BIG DATA MODELLING OPPORTUNITIES IN AGROFORESTRY AND M23: DYNAMIC MANAGEMENT TOOL FOR AF SYSTEMS AT FARM LEVEL

www.agroreforest.eu

REFOREST

Organisation: Organic Research Centre
Department: Agroforestry

ORGANIC RESEARCH CENTRE

M19

Report on big data modelling opportunities in AF

Date 11.06.2025
Doc. Version 05

Funded by the European Union

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101060635 (REFOREST). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for them.

UK Research and Innovation

UK partners are funded by UK Research and Innovation (UKRI) under UK government's Horizon Europe funding guarantee [grant number 10039700].

Document Control Information

Settings	Value
Milestone Title	Report on big data modelling opportunities in AF
Work Package Title	Monitoring and Verification
Milestone number	M19
Description	A report on big data modelling opportunities in agroforestry
Lead Beneficiary	ORC
Lead Authors	ORC – Colin Tosh
Contributors	CZU - Singh Arunima, Martin Mokros, Kottilapurath Surendran Gokul
Submitted by	Colin Tosh
Doc. Version (Revision number)	05
Sensitivity (Security):	Low
Date:	11/06/2025

Document Approver(s) and Reviewer(s):

NOTE: All Approvers are required. Records of each approver must be maintained. All Reviewers in the list are considered required unless explicitly listed as Optional.

Name	Role	Action	Date
Martin Lukáč	CZU Lead Beneficiary	Approved	11/06/2025

Document history:

The Document Author is authorized to make the following types of changes to the document without requiring that the document be re-approved:

- Editorial, formatting, and spelling
- Clarification

To request a change to this document, contact the Document Author or Owner.
Changes to this document are summarized in the following table in reverse chronological order (latest version first).

Revision	Date	Created by	Short Description of Changes
05	11.06.2025	CZU – Martin Lukáč	Minor edits
04	09.06.2025	ORC - Colin Tosh	Revision based on CZU comments
03	06.06.2025	CZU - Martin Lukáč	Full review
02	04.06.2025	CZU - Eva Májová	Minor edits
01	30.05.2025	ORC - Colin Tosh	First version

Configuration Management: Document Location

The latest version of this controlled document is stored in https://czuvpraze.sharepoint.com/teams/fld-t-reforest/Sdilene%20dokumenty/Forms/AllItems.aspx.

Nature of the deliverable		
R	Report	x
DEC	Websites, patents, filing, etc.	
DEM	Demonstrator	
O	Other	

Dissemination level		
PU	Public	x
CO	Confidential, only for members of the consortium (including the Commission Services)	

ACKNOWLEDGEMENT

This report forms part of the deliverables from the REFOREST project which has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101060635. The Community is not responsible for any use that might be made of the content of this publication.

More information on the project can be found at: http://agroreforest.eu/

COPYRIGHT

DISCLAIMER

TABLE OF CONTENTS

EXECUTIVE SUMMARY

With the advent of large cross-European soil data sets and continuous satellite monitoring of the Earth's surface by satellites, the possibility arises of integrating these very large data sets with modern machine learning methods to develop predictive models of soil carbon for low-cost soil carbon monitoring.

This report presents the development of advanced Big Data–driven convolutional neural network (CNN) models in WP4 of the ReForest project to predict soil organic carbon (SOC) content and plant biodiversity across Europe. Using multispectral Sentinel-2 imagery processed in Google Earth Engine, two V1 models were trained: a categorical SOC predictor on 18,000 LUCAS 2018 topsoil samples, and a continuous biodiversity predictor on 22,000 GBIF plant-richness points. Both achieved a four-fold performance improvement during training, with the SOC model correctly classifying the true SOC category 40 % of the time (±1 category 80 % of the time) and the biodiversity model reaching a mean error of ~100 species per 5 km² on unseen data and particularly strong in common agricultural landscapes.

Building on Living-lab deployments in the Czech Republic, Denmark and Germany, the SOC model was enhanced in V2 by integrating CORINE land-use, European Soil Database and ERA5 climate inputs; expanding dense-layer capacity; adopting a mixed MAPE–MPE loss function; and shifting to a continuous output. These refinements reduce mean percentage error to 20–30 % within the crucial 0–5 % SOC range, enabling high-definition soil carbon mapping for targeted farm-level interventions.

A critical review of related European agroforestry applications highlights both opportunities and limitations. Zellweger et al. (2022) combined allometric modelling and Random Forests to estimate that ~17 % of UK tree carbon lies outside forests. The Copernicus HRL Small Woody Features 2018 product claims ≥ 80 % thematic accuracy but under-detects linear features in established agroforestry systems. The UK Trees Outside Woodland Map, relying on LiDAR height models, Sentinel imagery and rule-based GIS, achieves > 95 % detection but only ~ 65 % classification accuracy. Similarly, the UKCEH Hedgerows layer reports 96 % length accuracy but lower height classification accuracy. Numerous EU-funded initiatives—LANDSUPPORT, DigitAF, AGFORWARD, NextLand and REFOREST—are advancing Big Data approaches, yet "on-the-ground" feedback underscores the need for co-creation with end users to ensure practical, farmer-focused tools.

LIST OF ACRONYMS AND ABBREVIATIONS

Abbreviation	Definition
SOC	Soil Organic Carbon
CNN	Convolutional Neural Network
LLM	Large Language Model
LUCAS	Land Use/Cover Area frame Survey
GBIF	Global Biodiversity Information Facility
GEE	Google Earth Engine
CORINE	Coordination of Information on the Environment
ERA5	ECMWF Reanalysis 5th Generation
MAPE	Mean Absolute Percentage Error
MPE	Mean Percentage Error
HRL	High Resolution Layer
NDVI	Normalized Difference Vegetation Index
GIS	Geographic Information System
LiDAR	Light Detection and Ranging
UKCEH	UK Centre for Ecology & Hydrology
NCEA	Netherlands Commission for Environmental Assessment
FP7	Seventh Framework Programme
EEA-39	European Environment Agency region (39 countries)
FWF	Farm Woodland Forum

LIST OF FIGURES

1. INTRODUCTION

Anyone who has ever gone for a walk in a woodland will be familiar with the carbon-rich soils that that high densities of trees produce under them through leaf fall and other processes, but what of agricultural systems where trees occur at lower density or in rows running through the field with conventional agricultural land in between rows? Do these carbon accumulation benefits extend to this type of agricultural land that is known as agroforestry?

This question has attracted a considerable number of reviews and meta-analyses of agroforestry and soil carbon in temperate regions. Mayer et al., (2022) concluded that temperate agroforestry systems consistently enhance soil organic carbon (SOC) stocks compared to conventional agriculture: a meta-analysis of 61 observations found average SOC sequestration rates of 0.21 ± 0.79 t C ha^{-1} yr^{-1} in topsoils (0–20 cm) and 0.15 ± 0.26 t C ha^{-1} yr^{-1} in subsoils (20–40 cm), with hedgerows achieving the highest gains (0.32 ± 0.26 t C ha^{-1} yr^{-1} in topsoils and 0.28 ± 0.15 t C ha^{-1} yr^{-1} in subsoils) and SOC stocks exceeding controls in over 70% of topsoil and 81% of subsoil comparisons. Overall, agroforestry can boost SOC by 30–80% relative to treeless systems and is recognized as one of the most promising agricultural practices for restoring degraded lands, providing ecosystem services, and contributing to climate change mitigation in temperate zones (Mayer et al., 2022; Shi et al., 2018).

Meta-analyses such as these are the culmination of a huge amount of field effort involving physical soil sampling and analysis reported in primary papers. With the advent of cross-European soil data sets such as the LUCAS 2018 topsoil data set (https://esdac.jrc.ec.europa.eu/content/lucas-2018-topsoil-data) and continuous monitoring of earth's surface by satellites such as Copernicus (https://dataspace.copernicus.eu/explore-data/data-collections/sentinel-data/sentinel-2), the possibility arises of integrating these very large data sets with modern machine learning methods to develop predictive models of soil carbon for low-cost soil carbon monitoring.

"Big Data" typically refers to data sets and operations with high Volume, Velocity, and Variety (the Three Vs model (Laney, 2001). While there is no strict definition on how high Volume, Velocity, and Variety must be to qualify as Big Data, the CNN described in this report routinely works on imagery datasets of 1TB in size, and many other models described later in the report operate on even bigger datasets. Undoubtedly, the popularity of Big Data has been driven by the rise of machine learning, including techniques such as Random Forests, Convolutional Neural Networks (CNNs) and Large Language Models (LLMs).

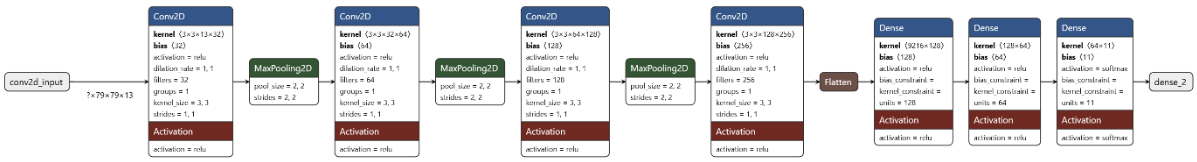
Machine learning applications rely on large data quantities due to their high capacity and the use of generalisation. Models can learn small data sets perfectly and very easily, but commonly learn only that data set and are unable to generalise to similar but slightly different data sets. As the size of the data set increases, the ability of a model to generalise also increases. Generalisation is probably the key usable property of machine learning models. Consider, for analogy, a school student who is asked to memorise and understand a single sentence in a book. He/she will simply memorise the words, and his/her ability to apply this learning to new scenarios is low. Next, consider a student who is asked to learn and understand a whole chapter of a book. In the process of learning and understanding the text, key insights will emerge that can be applied to chapters in completely different books.

Models of the size and complexity outlined in this document are rarely “finished” and are typically subject to continuing development. This report outlines three models developed in WP4 of the REFOREST project: V1 soil carbon and biodiversity prediction models and a V2 soil carbon prediction model incorporating additional land use and climatic data sets and switching to a more refined continuous output (Figure 1). It then proceeds to discuss other models developed in Europe that also rely on very large volumes of data. The report also provides some general conclusions.

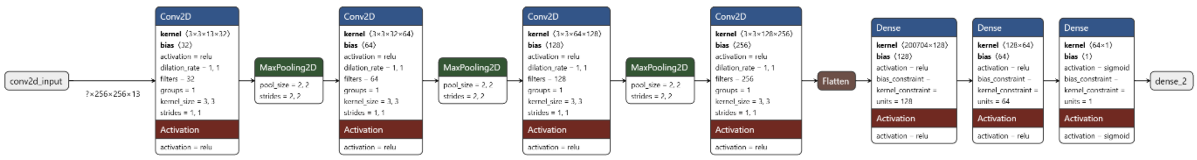
2. V1 CARBON AND BIODIVERSITY PREDICTION MODELS

Creation of these models starts with satellite image preparation for feeding into the CNN neural network. We used Sentinel 2 1-C images prepared in Google Earth Engine (GEE). These GeoTiff images have 13 bands, each corresponding to a different electromagnetic frequency, both within and outside the visible spectrum and are filtered for cloud cover in our implementation. In the case of the topsoil carbon prediction model, we took each of around 18,000 coordinates corresponding to points sampled in the LUCAS 2018 topsoil data set and fed these into GEE. A square snipped satellite image 500 m x 500 m centred at each coordinate was created and downloaded. For the biodiversity model, we took coordinates from the GBIF European plant diversity database: a random selection of around 22,000 points from Spain, Sweden, Switzerland and the Netherlands, and a 5 km x 5 km square centred on each coordinate was snipped and saved.

A) Carbon predictor V1



B) Biodiversity predictor V1



C) Carbon predictor V2

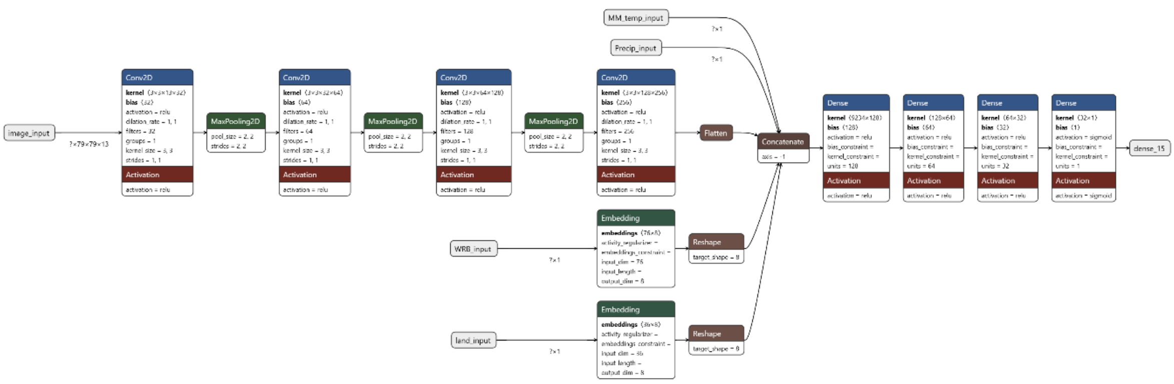


Figure 1: Detailed structural diagrams of currently completed CNN models

We used a larger sample area in the case of plant biodiversity (species richness, more specifically) because data in the GBIF database are quite sparse with regard to geographic area, and these dimensions ensured that we got few squares with no data in them.

These data sets, image sets and soil carbon and plant species richness values corresponding to each image, then become the input and output of the models as shown in Figure 1. These models, in essence, are trained by adjusting their thousands of parameters to match each image with its appropriate output value.

CNNs consist of two main parts. Image processing or convolutional layers take the raw image and extract relevant features. This information is then passed to the dense layers. These are more traditional neural networks that take inputs and translate them into decision-making behaviour: "The image just passed into the network shows 2% soil carbon", "The image just passed into the network shows 100% plant species", and so on.

Both carbon and biodiversity V1 prediction models show modest but useful levels of performance. The carbon model, which predicts in categories of 1% SOC between 1-10% and has an extra category for >10% values, improves in performance around 4-fold during training and on unseen data predicts the correct SOC category around 40% of the time, selecting the correct category or one category out around 80% of the time. The considerable improvements to the model in V2 are described below. The V1 biodiversity model provides continuous, not categorical, output and also shows an improvement level of around x4 during training, with a mean error of around 100 plant species per 5kmx5km area on unseen data. It should be noted, however, that the model performs much better than these headline figures would suggest on the most common types of landscapes in Europe, such as agricultural environments. Performance is "dragged down" by the smaller number of rarer landscape types present in the image set.

Online interactive versions of these models are available for use at the following developer links: https://drive.google.com/file/d/12KTf_-hSeN7rwgkLpZQQV82sg2cnz2gs/view?usp=drive_link

3. PRACTICAL APPLICATIONS OF THE V1 MODELS IN REFOREST

We have used these V1 models in several REFOREST agroforestry Living labs to produce coarse soil carbon maps of living lab farms and to provide estimates of living lab contributions to local biodiversity.

For carbon mapping, farms were sampled in 5-10m grids, satellite imagery gathered for each sample point and fed through the trained model described above. Some soil carbon maps from living labs are shown in Figure 2.

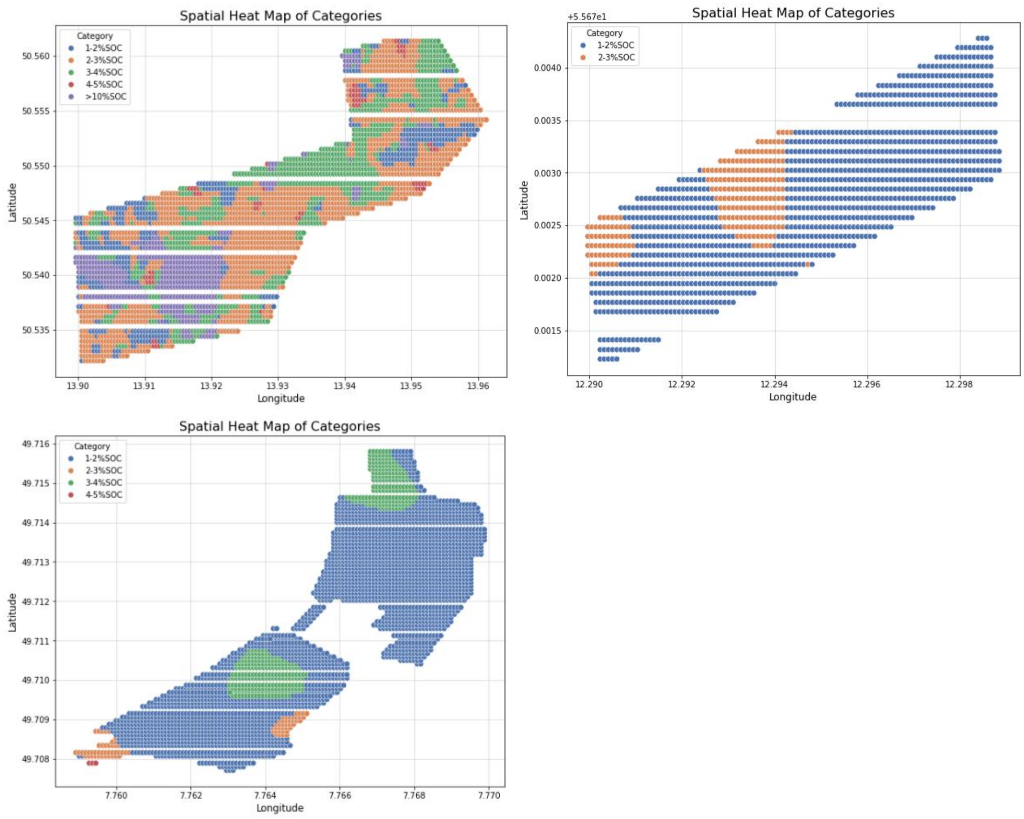


Figure 2: Soil carbon maps from REFOREST living labs in the Czech Rep (top left), Denmark (top right), and Germany (bottom left). Landscape features showing correlations with soil carbon content can be viewed at Google Maps using the axes coordinates.

Use of the biodiversity model on REFOREST living labs takes a more indirect approach as the spatial window of the model (5kmx5km) is typically much greater than the area of the farms. We have trialled image manipulation to circumvent this problem. Using Python scripts, we have "cut out" the area of each living lab from satellite images and replaced this area with areas of zero plant diversity, such as North African deserts. One such manipulated image containing the German living lab in REFOREST is shown in Figure 3.

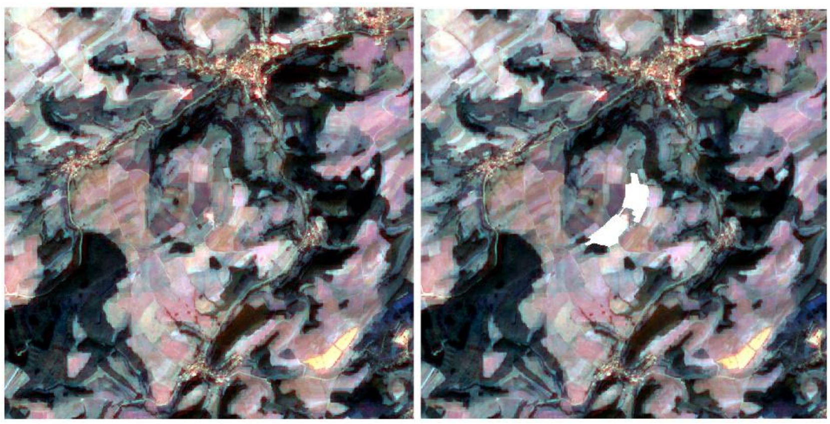


Figure 3: Use of the biodiversity V1 model has involved assessing unmanipulated images (left) and images with the farm area replaced by imagery of areas with zero biodiversity, such as North African deserts (right).

By running the manipulated images through the model and comparing plant species richness predictions to those made with the manipulated image, the number of unique species contributed by agroforestry practices in the living lab to the landscape can be inferred by subtraction. So far, this approach appears promising, but feedback has mainly been by word of mouth from farmers, as a whole site biodiversity assessment has not been completed at the time of writing. It has been predicted that the German living lab contributed 100 unique species to the local 5km x 5km area. The biodiversity expert Paweł Radzikowski states: “In the case of German LL, it is possible that about 100 species are unique to small areas, because tree and crop species have been included. Mostly they represent rare plant species, like fruit, nut and nectar trees of foreign origin, so they are not present in the surrounding landscape.” The Danish living lab, on the other hand, is predicted to contribute no unique species to the landscape, which is also plausible as it focuses on relatively standard cereal species and wood bioenergy crops likely to be present in the wider environment.

4. IMPROVEMENTS TO THE CARBON V1 MODEL

Improvements to the biodiversity V1 will also be made, very likely using the same approach as described below. However, the carbon model has been prioritised as web analytics, as provisional online versions of the model indicate there is more user interest in this model.

Additional data sets have been added to the training process. For each image, land use type (from the CORINE EU data set), soil type (WRB soil type from the European Soil Database v2.0), and ERA precipitation and temperature data are also input into the network at the later dense layer processing stage (see Figure 1). To accommodate this extra information, the capacity of dense layers has been increasing by adding a single 32-unit layer late in processing. Following feedback at the Second European Farm Carbon Summit, the output of the network has also been switched to a continuous output to allow more precise, fine-grained predictions. Finally, and most fundamentally, the loss function during training has been changed to mixed MAPE-MPE. Previously (V1), the loss function that was used focused on absolute error, which may have been pulling performance away from the most numerous and relevant samples within the 0-5% SOC range. The mixed model gives equal emphasis to small absolute (but potentially large relative) error, and the MPE component ensures that deviation from actual predictions is not biased but scattered both above and below real values.

This model produces a mean percentage error of around 50% overall, but the error is much lower (20-30%) within the most numerous and agriculturally relevant 0-5% SOC range. These levels of error mean that a real landscape with 1% SOC will usually be predicted at 0.8 or 1.2%, and a 2% soil predicted as 1.6 or 2.4%. This level of accuracy can give a useful high-definition soil carbon map across farmland to help farmers decide where effort should be focused to improve carbon levels. It also enables dependable tracking of C content change over time. Work is underway to incorporate this new model into the online interactive and should be completed at the time of review of this document.

5. OTHER BIG DATA APPLICATIONS IN EUROPEAN AGROFORESTRY

Clearly, it is desirable to develop models of agroforestry aboveground and tree root carbon, but WP4 has so far been unable to undertake this task effectively due to the lack of open access, cross-European wood volume/biomass data gathered using direct modelling techniques such as LiDAR. One approach we considered to circumvent this issue, but ultimately rejected, is the use of indirect modelling techniques such as allometric modelling to determine woody biomass, as exemplified by the UK's Woodland Carbon Code. Zellweger et al. (2022) used UK forest species inventories, satellite imagery and other environmental variables along with biomass predictions using the Woodland Carbon Code (woodlandcarboncode.org.uk) to develop a Random Forest predictive model of woody biomass outside forests (loosely "agroforestry"). They calculated that around 17% of the UK's tree carbon stock is held by trees outside forests. This use of indirectly modelled data to create new models presents a challenge: should we use indirect, often multiprocess modelling data, where each step of the modelling process can introduce error, to produce another predictive model? The availability of extensive empirically derived data sets on soil carbon, such as the LUCAS 2018 topsoil data set (esdac.jrc.ec.europa.eu/content/lucas-2018-topsoil-data), persuaded us that it would be more fruitful to focus on agroforestry's impact on soil carbon.

Another notable foray into big data by European Agroforestry is the HRL Small Woody Features 2018 Product (Copernicus Land Monitoring Service User Manual Consortium, 2021; https://land.copernicus.eu/en/products/high-resolution-layer-small-woody-features/small-woody-features-2018). This is a GIS-based product of small woody features (linear woody features and tree patches) covering the EEA-39 region. It was produced using a number of computational methods. The core component is a large data set comprising the Pleiades 1A/1B, SuperView-1, KOMPSAT-3/3A and PlanetScope acquisitions. These images are interpreted using a mixture of automated feature detection algorithms and a mixture of supervised and unsupervised machine learning (Random Forests). Previous maps covering smaller and different areas are also used as examples. This product claims ≥ 80 % thematic accuracy; however, casual use by the author suggests that it fails to detect many clumped and linear woody features in old and well-defined agroforestry systems in the UK, including the well-known Wakelyns (wakelyns.co.uk) site. Further refinement of the detection process to make it fit for agroforestry is therefore needed.

A similar product has been launched in the UK as the UK Trees Outside Woodland Map, which is available as an interactive product and a standalone GIS application (https://ncea.maps.arcgis.com/apps/instant/sidebar/index.html?appid=cf571f455b444e588aa94bbd22021cd3) (Freddie Hunter et al., 2025). This product was produced by Forest Research and unlike the other models discussed so far did not use machine learning at all in its construction. Instead, a LiDAR-derived tree height model was used in association with Sentinel imagery and NDVI vegetation detection and conventional map filtering, i.e. rule-based geoprocessing alone. The product claims tree feature detection rates of over 95%, but classification of tree features has a lower accuracy at around 65%. Again, while this product seem superficially to offer almost unlimited opportunities for physical and functional analysis of the agroforestry landscape, opinion on the ground among UK agroforestry farmers at least has been more muted, with the product failing to detect features in some of the UK best known agroforestry sites (this conclusion was drawn from a thread on the UK's Farm Woodland

Forum – FWF). Another product showing a similar reliance on LiDAR-derived canopy heights and deterministic GIS operations is the UKCEH Land Cover Plus: Hedgerows (2016–2021) which identifies hedgerow locations and lengths, determines their height, and allocates feature types to the identified hedgerow, with a length id accuracy of 96% but a considerably lower height classification accuracy.

6. SUMMARY

Many European initiatives are using Big Data approaches with an emphasis on multispectral satellite imagery and machine learning to automate landscape feature detection and quantification. We have outlined processes we are most familiar with, but a number of EU funded projects are active in this area, including: LANDSUPPORT (Horizon 2020, Grant 774234), DigitAF (Horizon Europe, Project 101059794), AGFORWARD (FP7-613520), NextLand (Horizon 2020, 869520), and of course ReForest (Horizon Europe, Project 101060635). While these new tools offer exciting research possibilities, personal experience suggests that "on the ground" users, such as agroforestry farmers, are less enthusiastic, commonly claiming maps miss features even in mature agroforestry sites. It may be that future work in this area could benefit from a co-creation approach where algorithm development goes hand in hand with farmer feedback to create products that are farmer-focused and of genuine use to them.

The accuracy of automated landscape assessment tools will increase further with increasing data availability and centralised GPU processing facilities in the EU. More precisely, semi-automated quantifications of landscape features can be achieved with near-field techniques (also being pioneered in REFOREST WP4) like drone image capture, but these involve extra effort and cost on the part of the farmer.

APPENDIX: REFERENCES AND RELATED DOCUMENTS

ID	Reference	Source or Link/Location
1	Copernicus Land Monitoring Service. User Manual Consortium. (2021). Small Woody Features 2018 and Small Woody Features Changes 2015-2018.	https://land.copernicus.eu/en/technical-library/high-resolution-layer-small-woody-features-2018-product-user-manual/%40%40download/file?utm
2	Freddie Hunter, Ben Ditchburn, Nancy Burns, & Conor Strong. (2025). NCEA: National Trees Outside Woodland Map Method and User Guide Report.	https://environment.data.gov.uk/file-management-open/data-sets/b01e513d-8aae-4098-98b1-6524a33f0767/files/TOW_RELEASE_V1_NCEA_Report.pdf
3	Laney, D. (2001). 3D Data Management: Controlling Data Volume, Velocity and Variety (Issue 6).	https://diegonogare.net/wp-content/uploads/2020/08/3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf
4	Mayer, S., Wiesmeier, M., Sakamoto, E., Hübner, R., Cardinael, R., Kühnel, A., & Kögel-Knabner, I. (2022). Soil organic carbon sequestration in temperate agroforestry systems – A meta-analysis. Agriculture, Ecosystems and Environment, 323.	https://doi.org/10.1016/j.agee.2021.107689
5	Shi, L., Feng, W., Xu, J., & Kuzyakov, Y. (2018). Agroforestry systems: Meta-analysis of soil carbon stocks, sequestration processes, and future potentials. Land Degradation and Development, 29(11), 3886–3897.	https://doi.org/10.1002/ldr.3136
6	Zellweger, F., Flack-Prain, S., Footring, J., Wilebore, B., & Willis, K. J. (2022). Carbon storage and sequestration rates of trees inside and outside forests in Great Britain. Environmental Research Letters, 17(7).	https://doi.org/10.1088/1748-9326/ac74d5

REFOREST

Organisation: Rheinische Friedrich-Wilhelms-Universität Bonn
Department: Institute of Crop Science and Resource Conservation Horticultural Sciences

M23

Dynamic management tool for AF systems at farm level

Date 23.06.2025
Doc. Version 03

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101060635 (REFOREST). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Executive Agency (REA). Neither the European Union nor the granting authority can be held responsible for them.

Funded by the European Union

UK Research and Innovation

UK partners are funded by UK Research and Innovation (UKRI) under UK government's Horizon Europe funding guarantee [grant number 10039700].

Document Control Information

Settings	Value
Milestone Title	Dynamic management tool for AF systems at the farm level
Work Package Title	Integration and Innovation
Milestone number	M23
Description	A report on dynamic management tool for different agroforestry systems at farm level
Lead Beneficiary	UBO
Lead Authors	UBO – Prajna Kasargodu Anebagilu, Andrew Marcil, Simon Swatek, Marcos Jiménez Martínez, Eike Luedeling
Contributors	DeFAF, OSA
Submitted by	Prajna Kasargodu Anebagilu
Doc. Version (Revision number)	03
Sensitivity (Security):	Low
Date:	23/06/2025

Document Approver(s) and Reviewer(s):

NOTE: All Approvers are required. Records of each approver must be maintained. All Reviewers in the list are considered required unless explicitly listed as Optional.

Name	Role	Action	Date
Martin Lukáč	CZU Lead Beneficiary	Approved	23/06/2025

Document history:

The Document Author is authorized to make the following types of changes to the document without requiring that the document be re-approved:

- Editorial, formatting, and spelling
- Clarification

To request a change to this document, contact the Document Author or Owner.
Changes to this document are summarized in the following table in reverse chronological order (latest version first).

Revision	Date	Created by	Short Description of Changes
03	23/06/2025	UBO – Prajna Kasargodu Anebagilu	Final version
02	23/06/2025	CZU – Martin Lukáč	Minor edits
01	17/06/2025	UBO – Prajna Kasargodu Anebagilu	Initial version

Configuration Management: Document Location

The latest version of this controlled document is stored in https://czuvpraze.sharepoint.com/teams/fld-t-reforest/Sdilene%20dokumenty/Forms/AllItems.aspx

Nature of the deliverable		
R	Report	x
DEC	Websites, patents, filing, etc.	
DEM	Demonstrator	
O	Other	

Dissemination level		
PU	Public	x
CO	Confidential, only for members of the consortium (including the Commission Services)	

ACKNOWLEDGEMENT

This report forms part of the deliverables from the REFOREST project which has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101060635. The Community is not responsible for any use that might be made of the content of this publication.

More information on the project can be found at: http://agroreforest.eu/

COPYRIGHT

DISCLAIMER

TABLE OF CONTENTS

EXECUTIVE SUMMARY

Addressing complex decisions in agricultural management, especially in agroforestry, requires structured methodologies that incorporate scientific evidence and stakeholder input. Decision analysis (DA) provides a framework that enables the systematic exploration of options and their implications under uncertainty. This principle is applied in the development of a dynamic management tool for a catalogue of agroforestry systems, as described in this report.

To better address the diverse requirements presented by the decision-makers, we opted to use the tool to develop a catalogue of agroforestry tools, each tailored to specific system characteristics and stakeholder concerns. We have developed tools for apple agroforestry, fruit trees, and honey-based agroforestry systems, including traditional meadow orchards (Steureobstweise), walnut alley cropping with vegetables, and a silvopastoral system. Rather than being finalized products, these tools are intentionally maintained in a perpetual beta phase, following an agile development approach. This allows for continuous refinement based on user feedback and real-world application.

A key feature of the interface is its ability to provide immediate visual feedback, empowering users to make more informed decisions. Additionally, users can activate the Expected Value of Perfect Information (EVPI) function to assess how much it would be worth investing in acquiring additional data, thereby supporting evidence-based decision-making. With this tool, we want to support decision-makers by integrating diverse types of knowledge into a transparent and reproducible decision-making process.

To facilitate broader engagement, we have developed an intuitive user interface that makes the tools easily accessible to various stakeholders. The interactive nature of the interface not only simplifies user interaction but also encourages knowledge sharing, enabling users to better understand how different variables influence outcomes. We plan to continue enhancing the tools throughout the remainder of the project, and potentially beyond, through active collaboration with subject-matter experts.

The activities described in this report are a continuation of those outlined in Deliverable 6.1, with further elaboration and additional functionality introduced in Deliverable 6.2.

LIST OF ACRONYMS AND ABBREVIATIONS

Abbreviation	Definition
AF	Agroforestry
DA	Decision Analysis
EVPI	Expected Value of Perfect Information
INAGRO	Instituut voor Landbouw-, Visserij- en Voedingsonderzoek
NPV	Net Present Value
ORC	Organic Research Center
UI	User Interface
UK	United Kingdom

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Decision-making in agricultural and natural resource management is notoriously complex. Producers, planners, and policymakers must weigh agronomic performance, economic feasibility, environmental trade-offs, and socio-political constraints, often under severe data limitations, climatic and market uncertainty. Traditional modelling approaches typically address only a subset of these dimensions or treat uncertain parameters deterministically, resulting in recommendations that may appear precise but often lack robustness when real-world conditions deviate from the assumed scenarios.

To better address this complexity and account for the multitude of risks and uncertainties that farmers face, we have adopted a holistic decision analysis (DA) approach (Luedeling & Shepherd, 2016) in developing the dynamic agroforestry management tool for the ReForest project. DA is explicitly designed to support real-world decision-making under uncertainty. Rooted in prescriptive decision theory from operations research and economics, it integrates expert knowledge, empirical data, and stakeholder values into transparent, probabilistic models that evaluate the consequences of alternative options (Whitney et al., 2018).

One of the key strengths of DA lies in its ability to simulate outcomes probabilistically, providing a spectrum of possible futures in terms of distributions rather than a single deterministic prediction. This allows for more resilient and informed decision-making under uncertainty. Additionally, DA's inter- and transdisciplinary framework ensures that all relevant dimensions of a decision, biophysical, economic, institutional and social, are incorporated, as required by the decision-makers. It also addresses the common problem of data gaps by leveraging expert and stakeholder knowledge to complement limited field data, while also allowing for quantifying the uncertainty associated with these inputs.

By integrating all available information and embracing rather than simplifying uncertainty, DA ensures that critical system variables and interactions are captured. Moreover, the framework can compute the Expected Value of Perfect Information (EVPI) to help decision-makers determine where investing in additional data would yield the most significant improvement in outcomes. This makes DA not only scientifically rigorous but also practically valuable for guiding decisions in dynamic and data-scarce environments. Therefore, it has been adopted in the development of the dynamic management tool for agroforestry at the farm level.

This report explains how the DA approach is applied in the development of the dynamic tool. For a more detailed discussion of the DA approach, readers are referred to Deliverable 6.1. The key focus of this report is the catalogue of agroforestry tools, each tailored to specific system characteristics and management questions we received from the decision-makers. These tools are equipped with distinct functionalities to address the unique challenges and decision-making needs of various agroforestry systems. Illustrative results generated using the DA approach are also presented, demonstrating how the probabilistic framework supports informed decision-making.

Additionally, the report includes a brief overview of the user interface (UI) developed to support data collection and encourage interaction with the dynamic tool. This interface is designed to enhance usability, facilitate stakeholder engagement, and enable users, whether farmers, researchers, practitioners, or policymakers, to both contribute their knowledge and explore how different input variables affect outcomes. The design rationale behind the interface is discussed, with emphasis on improving accessibility, transparency, and collaborative learning throughout the decision-making process.

2. Dynamic Management Tool with Decision Analysis Approach

The DA approach provides a robust framework for evaluating agroforestry interventions, particularly in the face of uncertainty and varying stakeholder perspectives. Especially in the case of agroforestry, where biophysical interactions, long investment horizons, long-term benefits that are often difficult to anticipate and shifting policy incentives make conventional deterministic planning unreliable. The DA approach helps to address this complexity by providing tools to forecast outcomes under different scenarios, consider various costs and risks, and ultimately support informed decision-making. A comprehensive explanation of the DA approach is provided in Deliverable Report D6.1. This report focuses specifically on how the approach was applied in the development of the DA tool.

The first step in the DA approach is to clearly define the decision problem and assess all possible interventions or strategies. This begins with a structured exploration of the system's defining characteristics, i.e., the factors that differentiate options and influence outcomes. Through participatory engagement, the decision-maker, other stakeholders and decision analysts collaboratively construct the conceptual representation of the system, capturing the essential elements that influence the decision landscape. The comprehensive conceptual model presented in D6.1 is the result of this step.

This conceptual model is then translated into a mathematical model by adapting it to the farm and decision-maker-specific requirements. This mathematical model provides the foundation for quantitative analysis. Crucially, rather than assigning single-point estimates or relying on average values for the different input parameters identified in the mathematical model, the DA approach uses probability distributions to represent each parameter.

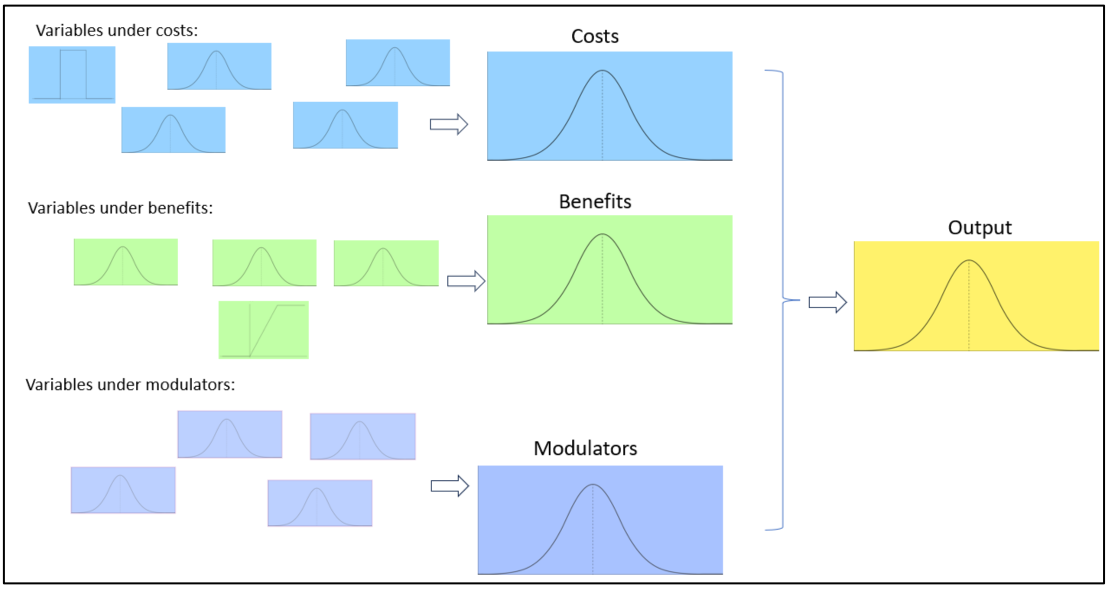


Figure 1: Schematic representation of input variables as probability distributions to generate a probabilistic outcome (Source: Lecture slides by Dr. Cory Whitney).

The use of average values is avoided as it can be misleading, as explained by the "flaw of averages" (Savage, 2002). By using the probability distribution for the input parameters, the uncertainty associated with the data collection is also taken into account. The data are collected from a literature review as well as expert estimates. In cases where empirical data are limited or unavailable, expert elicitation is used to define parameter values, typically expressed as 90% confidence intervals to reasonably reflect the associated uncertainty. This combined approach ensures that the model is well-parameterized while acknowledging and incorporating the inherent variability and knowledge gaps.

The mathematical formulations underlying the decision model are implemented in the R programming language (R Core Team, 2023), leveraging the specialized functions provided by the *decisionSupport* package (Luedeling et al., 2023) to perform probabilistic simulations. This package facilitates the integration of uncertainty into decision-making by allowing users to define input variables as probability distributions and simulate a wide range of possible outcomes.

Several key functions from the *decisionSupport* package (Luedeling et al., 2023) are used in the development of the dynamic agroforestry management tool. These include, but are not limited to:

- vv(): This function stands for "value varier" and is used to generate time series data that incorporates variability around a defined mean, based on user-specified ranges and a coefficient of variation. It allows for the introduction of uncertainty over time and supports the addition of trends to reflect dynamic changes.
- chance_event(): This function is used to model binary outcomes based on a specified probability; essentially simulating whether a particular event occurs or not. It is useful for incorporating discrete risks, such as the likelihood of a pest outbreak or the occurrence of extreme climatic events.
- gompertz(): This function models sigmoid growth based on the Gompertz function, commonly used for tree growth, such that a gradual increase in tree yield is introduced based on the user-provided yield estimates.
- mc_simulation(): This is the core simulation of the *decisionSupport* package. It performs Monte Carlo simulations, repeatedly sampling from the defined probability distributions of all input variables and calculating the outcome for each iteration. The result is a distribution of outcomes that reflects the combined effect of uncertainty across the system, allowing for robust comparison of decision options and clear visualization of associated uncertainty.
- evpi(): this function calculates the Expected Value of Perfect Information, i.e., the maximum amount a decision-maker should be willing to invest to eliminate uncertainty about a specific input variable. This helps prioritize data collection by showing where improved information would most enhance decision quality.
- plot_distributions(): This utility helps visualize the probability distributions of input variables and outputs, aiding interpretation and communication of uncertainty. It is useful for checking model assumptions and communicating the range of possible outcomes to stakeholders.

In the tool, the adoption of agroforestry is considered an intervention or alternative to the existing practice of conventional farming (baseline), i.e., the decision that the decision-maker is faced with. The outcome of the model is measured in terms of the overall economic performance of the two systems, as indicated by the net present value (NPV). It is calculated by summing the discounted net cash flows across all years of the simulation. The discounting process accounts for the time value of money, reflecting the principle that money available today is generally considered more valuable than the same amount received in the future due to the opportunity costs associated with it.

$$NPV = -C_0 + \sum_{i=1}^{t} \frac{C_i}{(1+r)^i}$$

where, C_0 is the cost of the system [€], C_i is the benefit in terms of cash flow in the year i [€], r is the discount rate defined by the decision-maker [%], and t is the duration of the simulation [years].

3. User Interface for the Dynamic Management Tool

As we aimed to model several distinct agroforestry systems to build a catalogue of dynamic tools tailored to farm-level decision-making, it was essential to start by basing the models on real-life experiences and expectations of farmers. These systems are highly diverse, and each component, whether trees, crops, or management practices, can significantly influence outcomes. Capturing this complexity required detailed, context-specific inputs from stakeholders. However, coordinating synchronous input sessions proved challenging due to the limited availability of experts and stakeholders, making it difficult to explain our approach and the modelling framework, align perspectives, and consistently elicit reliable parameter estimates.

To overcome this, we developed an interactive user interface (UI) for dynamic management tools for different agroforestry systems. The interface allows stakeholders and experts to contribute at their convenience, entering parameter ranges and uncertainties based on their knowledge and experience. Moreover, it provides immediate visual feedback, helping users understand the influence of their inputs on model outcomes. This not only ensures broader and more inclusive participation but also strengthens the credibility and usability of the tools by making the modelling process more transparent, intuitive, and grounded in practical applications. Using a dedicated UI to collect input ranges for the dynamic management tool offers several advantages over distributing an Excel template and requiring participants to manually fill in parameter cells.

Table 1: Key features of the user interface developed for the dynamic agroforestry decision-support tool, highlighting functionalities that enhance usability, flexibility, and user engagement.

Aspect	UI-based dynamic tool
Data integrity & validation	Built-in sliders, drop-downs, and numeric fields can enforce unit conventions and minimum–maximum bounds. Users cannot accidentally type text in a numeric cell or swap units (e.g., €/hectare vs. €/tree).
Clarity of definitions	Tooltip, and example (default) values appear contextually; an approach consistent with the need to have well-defined variables for the DA approach.

Aspect	UI-based dynamic tool
Instant feedback	A UI can generate real-time plots (e.g., probability distributions, cash flow, etc.) so users can immediately see whether their ranges are plausible.
Error handling	Error messages appear instantly, preventing faulty submissions.
Revision tracking & collaboration	Inputs are stored in a central database; changes by each expert are time-stamped.
Downloadable Input File	Allows users to edit or revisit their inputs later, especially when internet connectivity issues occur.
Downloadable Outputs	Model outputs, including probability distributions, cash flow, and cumulative cash flow, can be downloaded as image files for reporting, presentations, or further offline analysis.
Project Save and Load, Delete Function	Users can save their project sessions and reload them later, ensuring they do not need to re-enter data repeatedly.
Cross-platform consistency	Web UIs look and behave the same on Windows, macOS, and tablets.

3.1 Agile Development Process

The UI-based dynamic management tool was developed in alignment with the collaborative and iterative principles of the DA approach. Reflecting the evolving nature of real-world systems, we designed the models to be flexible, allowing for quick updates to input parameters, parameter ranges, stakeholder priorities, and risk factors as new evidence or insights become available. To support this adaptability, we adopt an agile development process, ensuring continuous refinement through user feedback and iterative improvement of both the model and its interface.

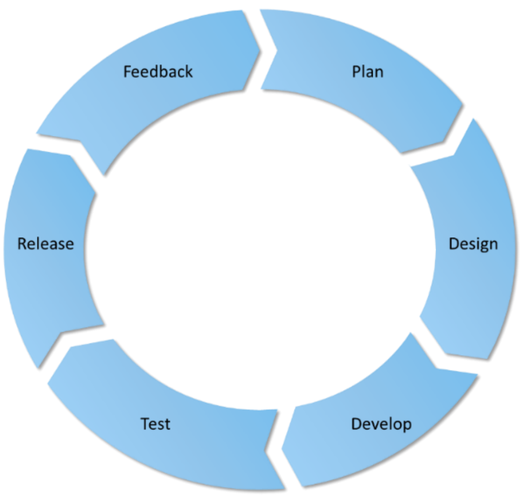


Figure 2: Iterative development cycle adopted in the creation of the dynamic agroforestry management tool, based on agile methodology.

The process includes planning, designing, developing, testing, releasing, and incorporating user feedback for continuous improvement. This iterative workflow is reflected in the following key components of our tool development strategy:

- Modular user interfaces for diverse agroforestry systems – We now publish working UI modules tailored to several system types (e.g., alley-cropping with carbon accounting, orchards with crop-rotation logic, design-scenario comparison). Stakeholders can explore each module, adjust the default parameter ranges, and inform us of which input variables or distributions require revision. This rolling feedback ensures that the model structure and outcomes remain aligned with the latest field knowledge, embodying the adaptive spirit of DA.
- Incremental functionality, guided by farmer priorities – The first build focused on essentials for the dynamic tool to function like capturing input ranges, running Monte-Carlo simulations, and reporting economic risk metrics, which many growers cite as the decisive factor. The latest release introduces a financial-support toggle that enables users to layer in national or CAP subsidies; this feature fulfils part of Deliverable 6.2 and demonstrates how new capabilities can be integrated into the core engine without disruption.
- Continuous learning cycle – Every version is a prototype. If a slider feels unintuitive or the output graph fails to answer a practical question, we rework it in the next iteration; nothing is treated as permanent. This rapid iterate-refine cycle ensures the tool remains user-driven and evolves rather than freezing into an early, sub-optimal design.

3.2 Catalogue of farm-level agroforestry systems

While the project has established connections with numerous farms through the Living Lab network (WP 1), we selected the agroforestry demonstration plot at INAGRO and the Mindrum farm from the UK Living Lab for simulation with the dynamic management tool, as our discussions revealed these systems to be innovative and distinct, making them ideal candidates for modelling.

Additionally, being based in Germany, we have collaborated with some agroforestry farmers outside the formal project network. To foster broader collaboration and knowledge exchange, we decided to include their systems as well. As a result, the tool also covers diverse German agroforestry configurations, including an apple alley cropping system with annual crops and multi-species fruit tree systems with honey production, with the traditional meadow orchard (Streuobstwiese).

This inclusive approach not only enriches the catalogue of modelled systems but also strengthens the project's outreach and practical relevance across different agroforestry contexts. A brief description of the systems, assumptions, and specific functionality covered for the system using the dynamic tool, along with illustrative results obtained, is provided for these four agroforestry systems.

3.2.1 INAGRO’s agroforestry demonstration plot, Belgium Living Lab

System description

INAGRO’s agroforestry demonstration plot, located on a gentle 1.4-hectare slope in Beitem, West Flanders (Belgium), exemplifies a well-structured walnut-based alley-cropping system. The system features rows of common walnut (*Juglans regia*) planted with 8 meters between trees within rows and 24 meters between rows, resulting in a planting density of approximately 36 trees per hectare. Each tree row is accompanied by a 3-meter-wide strip sown with flowering grasses, while the 21-meter-wide alleys in between are cultivated with a rotating sequence of high-value annual crops, including leek, carrot/celeriac, maize, potatoes, wheat, and field beans. The rotation sequence is leek → carrot/celeriac → maize → potatoes → wheat → field beans.

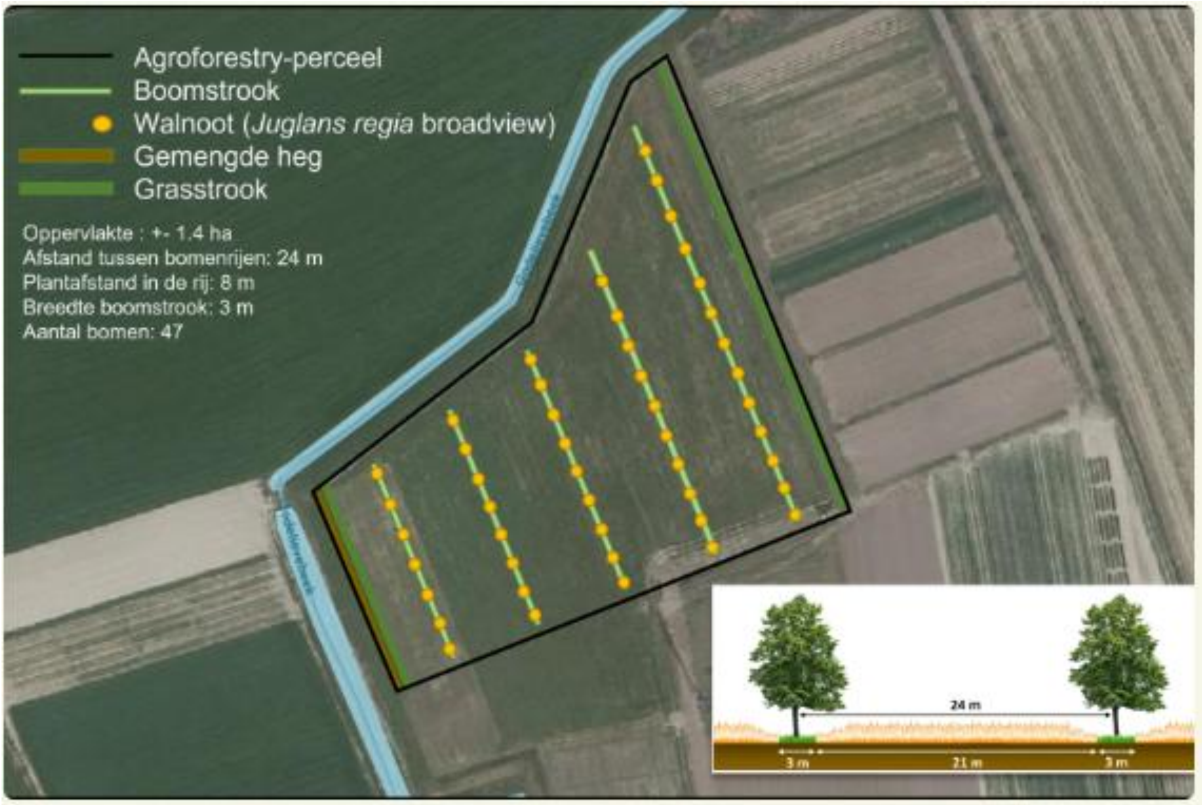


Figure 3: INAGRO's agroforestry demonstration plot.

To enhance biodiversity, landscape resilience and wind protection, the plot is flanked on both its eastern and western borders by mixed woody hedgerows. The eastern hedge was already present prior to the trial, while the western hedge was planted as part of the demonstration. This newer hedge features a double-row layout, 1.5 meters wide, with an estimated planting density of approximately 8,300 shrubs per hectare. It includes a diverse mix of native species such as common hawthorn (*Crataegus monogyna*), privet (*Ligustrum vulgare*), red dogwood (*Cornus sericea*), field maple (*Acer campestre*), guelder rose (*Viburnum opulus*), wood rose (*Rosa gymnocarpa*), dog rose (*Rosa canina*), and medlar (*Mespilus germanica*).

The soil is a fertile sandy loam, typical of the West Flanders region, an area known for its high land value due to high agricultural productivity. The walnut trees are intended for timber harvest at around

40 years of age, aligning the system with long-term production and ecosystem service goals. Overall, this demonstration site integrates productive cropping with ecological enhancements, offering a replicable model for multifunctional agroforestry in high-value farming regions. The objective of the demonstrative plot is to assess whether agroforestry can be profitable even within the context of highly intensive farming (i.e., not only intercropped with cereals, but also with vegetables, tubers and grain legumes). During its development, lessons learned from the experience will be shared with other farmers in the region, aiming to fill the gap in real-world examples of agroforestry management and its performance, thus making it an interesting plot to be simulated with the dynamic management tool. The dynamic tool developed for this system also calculates carbon dynamics in the soil, as well as above-ground and below-ground biomass, over several tree rotations. Other ecosystem services, specifically those benefiting from the prevention of soil erosion and groundwater recharge by trees, are also included in the tool.

Illustrative results

Suppose a farmer is not only focused on the absolute profitability of a system but is particularly interested in comparing the economic difference between maintaining conventional farming and adopting agroforestry. In that case, the agroforestry intervention may initially appear less favourable or on par with conventional farming.

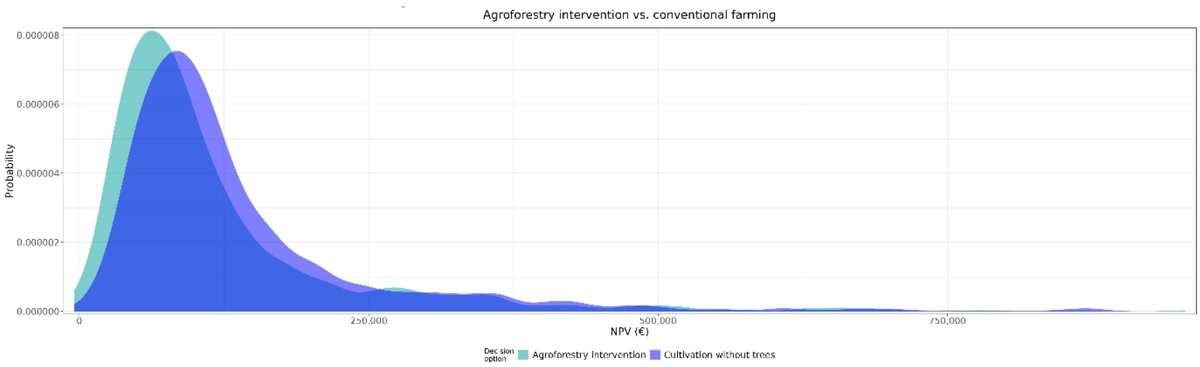


Figure 1 shows the Net Present Value (NPV) distributions of the decision to establish the alley cropping system (green) and the decision to continue farming without planting trees (blue) for the timescope of interest. The x-axis displays NPV values (i.e., the sum of discounted annual cash flows) and y-axis displays the probability of each NPV amount to occur (i.e., higer y-values indicate higher probability).

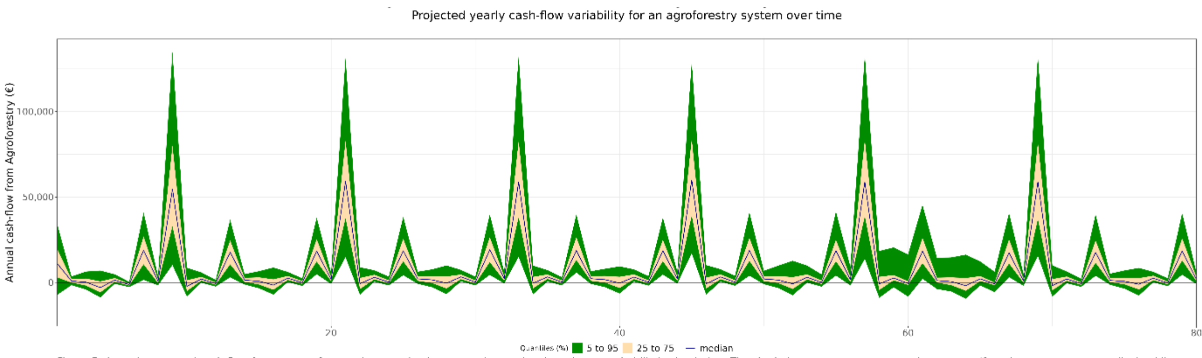


Figure 5 shows how annual cash-flow from an agroforestry intervention is expected to evolve, based on a probabilistic simulation. The shaded areas represent uncertainty ranges (from lower to upper quantiles), while the blue line shows the median outcome (expressed in €). While early years may involve negative cash flow, profitability tends to improve over time, with increasing stability. The graph highlights the long-term financial potential and risk spread of adopting agroforestry practices.

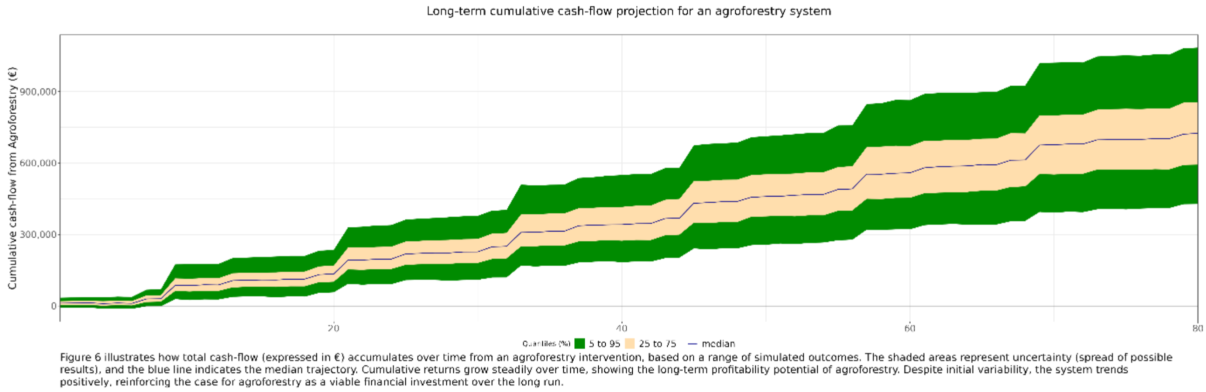


Figure 4: Illustrative result of net present value distributions of decision options, annual cash flow and cumulative cash flow of the INAGRO agroforestry demonstrative plot with default values and no financial support.

Context-specific factors strongly influence this outcome. The demonstration site is located in one of Europe's most fertile agricultural regions, where high-value crops like celeriac and leek are cultivated using intensive management practices, including substantial inputs of agrochemicals. These conditions enable crops to approach their maximum yield potential, making the opportunity cost of reducing arable land for tree planting particularly high. In such cases, even before considering possible impacts of tree-crop interactions, the loss of cropping area alone can translate into substantial revenue reductions, especially for crops with high market returns.

Online interactive UI for this system is available for use at: https://agtools.app/Walnut-Agroforestry/

3.2.2 Mindrum Farm, UK Living Lab

System description

This model is based on a prospective agroforestry system under consideration at Mindrum Farm, located on the Mindrum Estate in Northumberland, England. The farm operates under certified organic standards and follows a diversified mixed-enterprise model that integrates livestock production with annual cropping and small-scale managed woodlots. Enterprises include a primary ewe flock, a suckler-cow herd, and arable land managed on light to medium soils using annual crop rotations. The farm employs a regenerative farming strategy, incorporating practices such as vermiculture, biofertilizers, wildflower margins, and flexible tillage to improve soil health and ecosystem function.

As part of the ReForest project, Mindrum Farm is exploring the integration of agroforestry as a means to enhance system resilience and diversify long-term productivity. Agroforestry elements have already been partially implemented, and further interventions are currently being considered for a 14.97 ha arable parcel currently managed as monoculture cropland. In collaboration with the Organic Research Centre (ORC) as part of the project's Living Lab network, we were invited by the farm owner to provide quantitative decision support for two agroforestry designs, which we have modelled with the agroforestry dynamic management tool at the farm level. The objective was to assess the economic and biophysical implications of establishing woody strips under two layout scenarios:

- Agroforestry System 1 (AF1): This configuration features two 200 m long woody strips, each 15 m wide, consisting of short-rotation coppice species (primarily *Salix caprea*) surrounded by a buffer of native tree species within protective tree guards. The strips are oriented southwest to northeast, positioned perpendicular to the site's approximate 6° slope. Peripheral zones around the strips are to remain accessible for livestock grazing, enhancing multifunctionality.
- Agroforestry System 2 (AF2): This alternative design includes three 5 m x 300 m woody strips oriented along the slope (northwest-southeast) to disrupt both prevailing westerly winds and storm winds from the northeast. The strips combine a diverse selection of tree species with dense shrub layers, including Salix spp., and similarly incorporate livestock-accessible buffer zones.

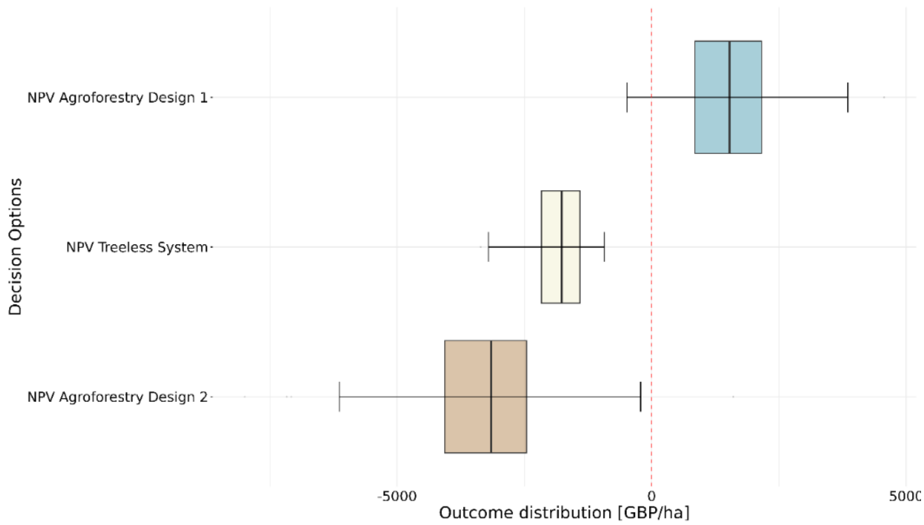
It is the first time that the design aspects of agroforestry are being modelled using the DA approach based dynamic tool. Within the dynamic tool created for this agroforestry system, we have considered both biophysical impacts, including wind and soil erosion control, shade provision, and understory productivity, and management considerations such as implementation complexity and time requirements. This system also incorporates crop rotation flexibility, which was embedded directly into the model logic. Two alternative rotation schemes were simulated to evaluate their impact on long-term system performance:

- Crop Rotation 1 (CR1): A five-year cycle consisting of three years of herbal ley followed by two years of winter wheat.
- Crop Rotation 2 (CR2): A six-year cycle with one year of herbal ley followed by winter wheat, spring barley, summer beans, and winter oats.

These rotations reflect the farm's organic standards and its commitment to soil regeneration and biodiversity enhancement. The ability to assess rotation-specific effects on long-term profitability and system resilience represents a key advancement in the modelling framework.

Illustrative results

The illustrative results when the tool is run at the default value suggest that AF2 is the more lucrative of the two agroforestry options, in addition to being more lucrative than maintaining the land as a treeless system (Figure 5).



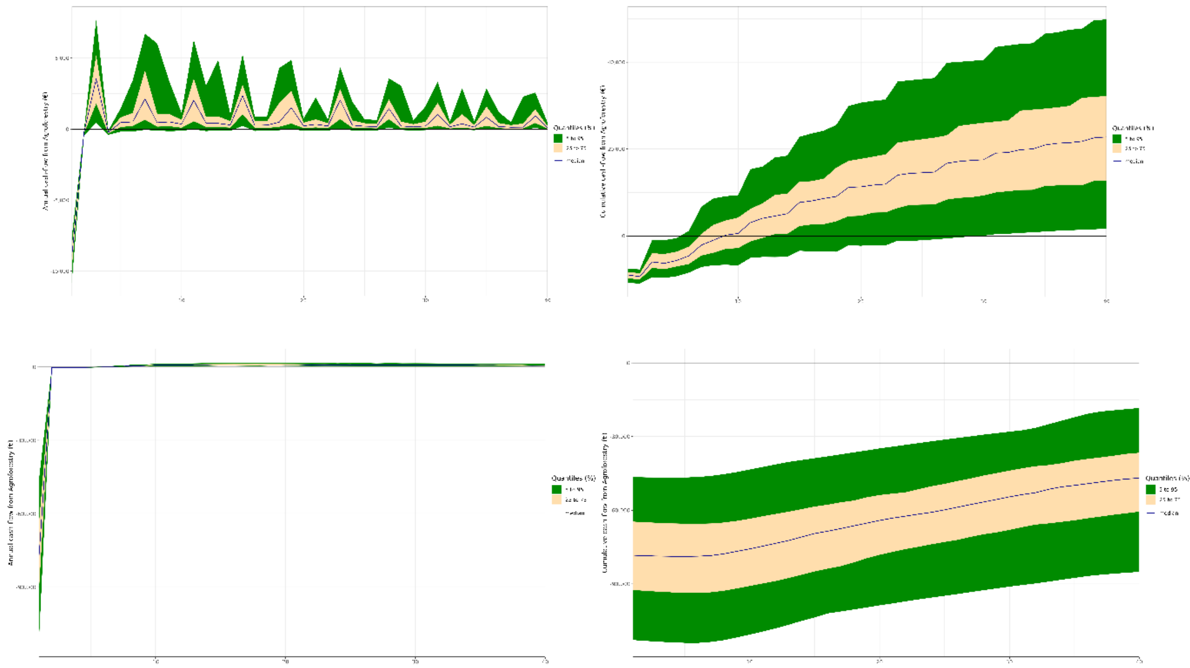


Figure 5: Illustrative result of net present value distributions of decision options, annual cash flow and cumulative cash flow of the two agroforestry designs for Mindrum farm with default values and no financial support.

A post hoc analysis revealed that the overall costs of the two systems were not significantly different; however, the increase in benefits in AF2 drove a higher overall NPV. This included important benefits such as a reduction in livestock stress from wind and rain, as well as increased access to woody forage (which research has shown to be highly beneficial to livestock health and vigor), resulting in a higher production of saleable meat compared to the AF1 and treeless systems. In this dynamic tool, the crop rotation scheme selected by the user also plays an important role in determining the overall NPV of the system.

Online interactive UI for this system is available for use at: https://agtools.app/Silvopastoral-Livestock/

3.2.3 Apple Agroforestry System, Germany

System description

This model is based on an existing agroforestry system that combines arable cropping with table apple production. The farm is located at 60 m above sea level in the Westphalian Bay in north-western Germany, characterized by a temperate oceanic climate with average temperatures of 10.2°C and annual precipitation of 780 mm.

The silvoarable alley cropping system encompasses 10.14 ha of arable field, with 5.6 % (0.57 hectares) planted with 473 apple trees of 9 different cultivars. The trees are arranged in 15 rows spaced 30 m apart, oriented north-south, perpendicular to the prevailing wind direction. Apple varieties were carefully selected to be suited to the intended low-input cultivation with minimal chemical inputs. No fungicides, herbicides or insecticides are planned to be used for plant protection. Codling moth (*Cydia pomonella L.*) control relies exclusively on strategic pheromone dispenser deployment.

Moderately vigorous rootstocks (M4, MM106, M25) were chosen to promote strong root development while maintaining manageable canopy heights for manual harvest. Tree spacing varies from 3.5-5 m within rows, depending on rootstock and cultivar growth characteristics. A drip irrigation system installed within tree rows ensures adequate fruit development while minimizing competition with row crops. The system is expected to reach maturity at 9-12 years, creating rows of low, wide-canopied apple trees that divide the arable field into alleys in which arable cropping is continued.

The arable component maintains the farm's original management approach, producing feed for the farm's pig fattening operation through a crop rotation of winter wheat, winter barley, rapeseed and maize (corn-cob-mix). Field management follows conventional practices enhanced with “regenerative” techniques, including a no-till approach to field cultivation.

The dynamic tool developed for this system incorporates several key assumptions regarding system stability and consistency in management. The established crop rotation is assumed to remain unchanged throughout the simulation period, providing a stable baseline for arable production estimates. Tree management risks, particularly those related to farmer inexperience, were addressed through specific model parameters rather than being excluded entirely. Potential management errors, such as faulty pruning, which could reduce yields or induce alternate bearing patterns requiring additional corrective measures, are mitigated through mandatory employee training, with associated costs incorporated in the model. To account for remaining uncertainties regarding cultivar-specific yield variations and alternate bearing cycles, wide value ranges were applied to apple yield estimates.

Within the tool, provision is made to acknowledge that fruit trees may cause slight reductions in arable yields due to resource competition, while simultaneously providing yield stabilization benefits during extreme weather events, such as prolonged droughts. Tree vulnerability to weather damage from late frost, hail and heavy winds is incorporated through yield reduction parameters, though only immediate effects (yield losses in the year of extreme weather occurrence) are modelled, excluding potential long-term impacts on tree productivity.

Illustrative results

Comparison of NPV distributions between the AF system and the arable baseline at default value reveals substantially higher uncertainty associated with the AF implementation, evidenced by the considerably wider NPV distribution compared to the baseline system’s narrow distribution. This increased uncertainty reflects the inherent complexity and long-term variability associated with integrating perennial fruit production into established arable operations.

Simulation results demonstrate that the majority of the decision NPV values are positive, indicating a high probability that the AF system represents the economically superior choice over the 30-year evaluated period. This finding suggests that despite increased uncertainty, the potential benefits of integrating apple production with existing arable operations outweigh the risks for this specific system configuration and regional context.

Online interactive UI for this system is available for use at: https://agtools.app/Apple-Agroforestry/

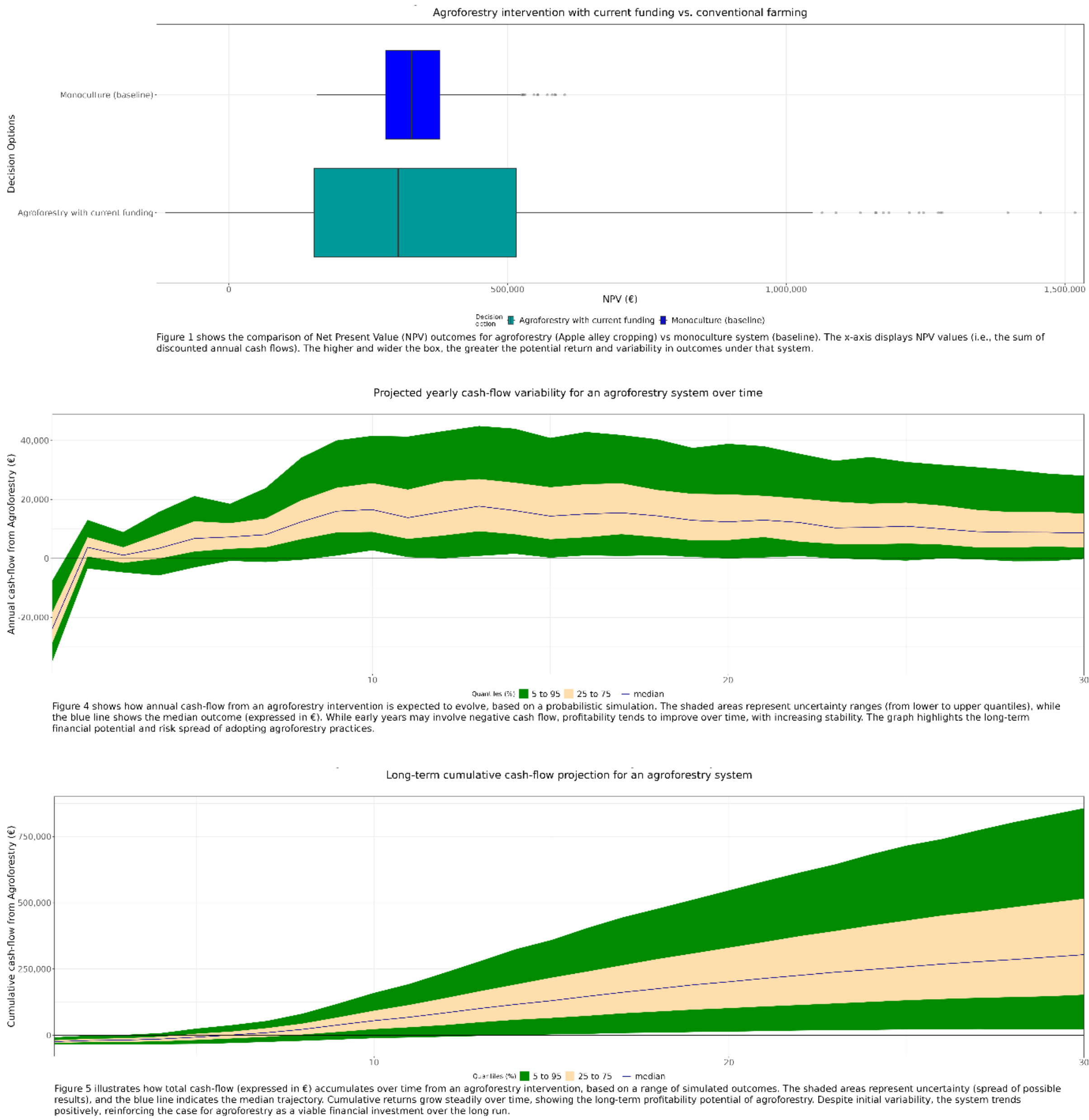


Figure 6: Illustrative result of net present value distributions of decision options, annual cash flow and cumulative cash flow apple alley cropping agroforestry in north-western Germany with default values and no financial support.

3.2.4 Multi-species fruit tree systems with honey production, and Streuobstwiese, Germany

System description

The last dynamic tool developed is based on a comprehensive AF consultation plan developed for a German farmer planning to integrate fruit trees, berry bushes and honeybee hives while transitioning from conventional to organic farming. This agroforestry system was planned by Ms. Frauke Ganswind from the Arbeitsgemeinschaft bäuerliche Landwirtschaft - Landesverband Nordrhein-Westfalen e.V., Germany. This model illustrates how the DA approach can assist farmers and agricultural consultants in planning agroforestry systems of varying complexities.

The farm is located in the Münsterland region, in north-western Germany, at 54 m above sea level on flat, non-sloped terrain. The site is characterized by waterlogged conditions that require drainage. The climate exhibits a mean annual precipitation of 659 mm and an average annual temperature of 9.7°C. Currently, the area is conventionally managed arable land with a crop rotation of maize, wheat, barley and soybeans. The transition plan involves establishing multiple integrated production systems across the field: a silvoarable fruit alley cropping system, a traditional meadow orchard (Streuobstwiese) and a hedgerow, all of which are designed with the beekeeping operation in mind to use synergistic effects.

Figure 7: Layout for the farm for which the multi-species fruit trees, honey production and Streuobstwiese are planned (Source: Report by Ganswind).

Seven woody strips are planned as the primary fruit production component in the alley cropping system. Raspberry serves as the main crop along the entire length of each strip, planted in 1.5 m wide cultivation strips. Each strip is flanked by 1 m wide grass strips on both sides to prevent trampling damage to the adjacent row crops during harvest, resulting in total strip widths of 3.5 m. On the eastern side of the strips, which do not require drainage and deeper root penetration is possible, two strips will be supplemented with Mirabelle plums at 12 m spacing, while the remaining five strips will feature edible rowan at 10 m intervals. A 0.5-hectare area is designated for traditional meadow orchard establishment, planted with heritage apple varieties. Trees will be spaced at 12 x 12 m intervals to ensure adequate light penetration to the understory meadow. The orchard will accommodate 39 trees with approximately 6 trees per variety. The southern boundary of the field, representing the farms' external border, will be planted with a conservation hedgerow for aesthetic reasons and to buffer drift from neighboring conventional fields. The hedgerow will consist of staggered rows planted 1 m apart, with 1 m spacings within rows.

The transition to organic farming coincides with an extended crop rotation designed to create synergistic effects with the planned beekeeping operation. The new crop rotation includes clover ley, wheat, buckwheat, rye, flax, soy and spelt. The beekeeping component is integrated across all system elements, utilizing nectar and pollen resources from flowering arable crops, fruit trees, raspberry bushes, meadow orchard and hedgerow plantings to support honey production as an additional enterprise.

The tool incorporates several assumptions, particularly regarding lesser-known speciality crops such as edible rowan fruit intended for distilling applications, where market data and production parameters are limited. Yield estimates and pricing for these crops were based on available literature and expert estimations. Beekeeping operation costs are modelled as proportional to honey harvest volumes from all components of the mixed AF system. This approach does not account for fixed costs, such as packaging materials, which occur regardless of production volume, potentially underestimating total beekeeping enterprise costs. The transition to organic farming introduces additional uncertainties regarding yield stability during the conversion period and potential pest management challenges. It is assumed that higher prices for organic products can be achieved from the first year of the transition, which is not in line with German organic certification standards, which require a conversion phase after which produce can be marketed as organic.

Illustrative results

Monte Carlo simulations performed with default input parameter values reveal increased uncertainty regarding the true economic outcomes of the integrated AF intervention compared to the relatively predictable baseline arable-only operation. The complex multi-enterprise system generates wider NPV distributions, reflecting the inherent variability associated with integrating multiple production components with different risk profiles and market dependencies.

Despite the increased uncertainty, simulation results demonstrate high confidence that the diversified AF system will outperform the conventional baseline system over the simulation duration. The multiple revenue streams from fruit production, honey sales and premium organic crop prices provide sufficient economic advantage to overcome the additional complexity and workload. The model illustrates how Decision Analysis frameworks can effectively evaluate complex agricultural transitions, providing quantitative support for farm- or plot-level decision-making when multiple production systems and management changes are considered simultaneously.

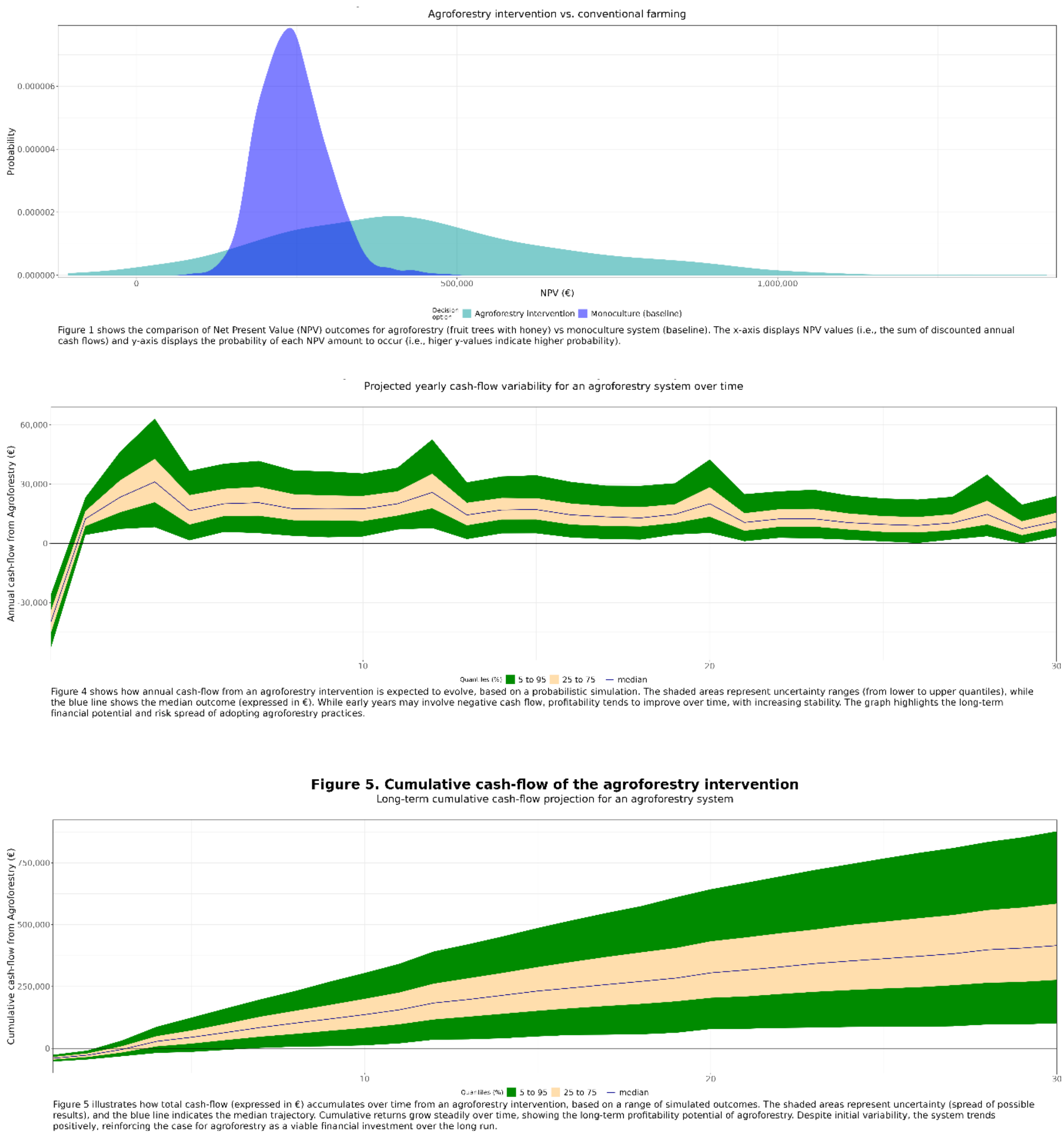


Figure 8: Illustrative result of net present value distributions of decision options, annual cash flow and cumulative cash flow for a complex multi-species fruit tree, honey and traditional meadow orchard agroforestry system in Germany with default values and no financial support.

Online interactive UI for this system is available for use at: https://agtools.app/Fruit-Honey/

4. Conclusion and Outlook

In this report, we provide a catalogue of dynamic management tools developed at the farm level for agroforestry systems, based on real-life systems. The application of the DA approach in developing the dynamic agroforestry management tool has proven to be a powerful method for supporting complex decision-making under uncertainty. By integrating probabilistic modelling, expert knowledge, and stakeholder input, the DA framework provides a structured and transparent approach to evaluating diverse agroforestry outcomes over extended time horizons. Unlike conventional models that rely on average values, DA captures the full range of possible outcomes, allowing users to assess trade-offs, risks, and long-term benefits with greater confidence.

To make this process more accessible and participatory, a user-friendly interface (UI) was developed, aligned with the collaborative and iterative spirit of DA. The UI enables stakeholders, farmers, researchers, and policymakers to interact directly with the tool, entering parameter estimates, adjusting system variables, exploring alternative scenarios, and instantly visualizing the outcomes. It facilitates data collection in decentralized, flexible settings, overcoming the logistical challenges of synchronous expert engagement. Moreover, features such as downloadable input/output files, project-saving options, and interactive EVPI analysis make it a practical and educational tool for end-users.

Together, the DA model and UI form an adaptable, evolving platform that not only enhances data quality and model relevance but also empowers users to make informed, resilient, and context-sensitive decisions. For farmers, it provides a clear picture of long-term economic and environmental outcomes under different agroforestry designs. For researchers, consultants and advisors, it provides a flexible modeling environment to simulate complex agroforestry systems, systematically incorporate expert input, and pinpoint specific areas where more targeted research is needed. For policymakers, the tool supports evidence-based planning by highlighting the implications of uncertainty, the benefits of acquiring additional information, and the importance of targeted policy incentives. The subsequent phase of work on the dynamic tool and its user interface, presented in Deliverable D6.2, builds directly on the foundation laid in this report and is especially relevant for policy development and strategic decision-making.

APPENDIX: REFERENCES AND RELATED DOCUMENTS

ID	Reference	Source or Link/Location
1	Luedeling, E., & Shepherd, K. (2016). Decision-Focused Agricultural Research. Solutions, 7, 46–54.	https://apps.worldagroforestry.org/downloads/Publications/PDFS/JA16154.pdf
2	Luedeling, E., Goehring, L., Schiffers, K., Whitney, C., Fernandez, E. (2024). decisionSupport: Quantitative Support of Decision Making under Uncertainty. R package version 1.114	10.32614/CRAN.package.decisionSupport https://cran.r-project.org/web/packages/decisionSupport/index.html
3	R Core Team (2023) R: A Language and Environment for Statistical Computing.	https://www.R-project.org/
4	Savage, Sam L., and Harry M. Markowitz. The Flaw of Averages: Why We Underestimate Risk in the Face of Uncertainty. John Wiley & Sons, 2009.	
5	Whitney, C., Shepherd, K., Luedeling, E. (2018). Decision analysis methods guide; Agricultural policy for nutrition. Working Paper No. 275. World Agroforestry Centre, Nairobi.	https://www.cifor-icraf.org/publications/downloads/Publications/PDFS/WP18001.pdf