Impact of land use on functional plant diversity - A new assessment method demonstrated in Germany

Master Thesis, Sven van Baren

Leiden University/TU Delft, Master Industrial Ecology

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Supervisors:

Dr. Laura Scherer, CML dept. of Industrial Ecology, Leiden University

Prof.dr.ir. Peter van Bodegom, CML dept. of Environmental Biology, Leiden University

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Abstract

Assessing the human impacts on biodiversity is important for conserving biodiversity. Life cycle assessment (LCA) is a tool to assess the impact product service systems have on the environment. To critically asses the human impact of land use on biodiversity in LCA, characterisation factors (CF) are needed to translate area and type of land use into loss of biodiversity. Most CFs are based on species richness but another biodiversity indicator, functional diversity (FD), better represents ecosystem functioning compared to taxonomic measures such as species richness. This study proposes a new method for calculating CFs, based on FD, for assessing impact of land use on plant biodiversity. To demonstrate the applicability of the method that is proposed, CFs were calculated based on data from Germany. The data was divided into four types, being land use, plant abundance, trait data and environmental data. The CFs developed show trends in impact on biodiversity in accordance with other studies. The proposed method in this study can guide in the development of more precise and geographically diverse CFs for assessing the impact of land use in biodiversity in LCA.

Keywords: Life cycle assessment, characterisation factors, biodiversity, land use, functional diversity, industrial ecology

1. Introduction

Biodiversity is defined as the diversity of all living organisms, ranging from genes to ecosystems (Swingland 2000). Biodiversity at all levels has been in decline for many decades as a result of human influences and it has been predicted to continue to do so in the 21st century (Butchart et al. 2010; Pereira et al. 2010). These influences can be specified into five impact categories being: climate change, overexploitation (e.g. overfishing), introduction of invasive species, pollution (e.g. nutrient pollution of nitrogen) and habitat change due to land use change, of which the latter has the biggest effect on terrestrial biodiversity (Millennium Ecosystem Assessment (Program) 2005; Pereira et al. 2010). All these impacts result in life (biodiversity) on earth declining and therefor calls for humanity to act and do something about it. However, scientific knowledge is needed to aid policy makers to develop a more sustainable use of the earth's resources and conserving biodiversity.

Products and services have a major impact on the environment, through their use of natural resources as well as their output into the environment such as emissions. To analyse the actual impact of product service systems on the environment, revealing potential improvement for sustainable development, there is the life cycle assessment (LCA) (Hellweg and Mila i Canals 2014). LCA takes a life cycle approach which means that it assesses all the inputs and outputs from and to the environment during the complete life cycle of a product system. Conducting an LCA consists of four different steps (Finkbeiner et al. 2006). In the first step the goal and scope of the assessment are set, defining the objective and boundaries of the assessment. The second step, called life cycle inventory analysis, identifies and collects all the inputs and outputs of a product service systems during its complete life cycle. This generally results in a long list of quantified values of emissions and resources, for example, the amount of CO_2 produced and the amount of land used. The third step, life cycle impact assessment (LCIA), groups all the emissions and resources into impact categories and expresses it in common impact units which makes it easier for comparison with LCA's of other product service systems (Hellweg and Mila i Canals 2014). The fourth step, the interpretation step, involves looking at the inventory analysis and impact analysis to answer the objective of the study.

To get from the second to the third step characterisation factors (CF) are used. CFs are conversion factors translating the values in the inventory analysis to the different impact categories in the LCIA. For example, CH_4 and CO_2 can be grouped and translated to Global Warming Potential expressed in CO_2-equivalent. The CFs for CH_4 and CO_2 are 84 and 1 *kg CO_2-eq/kg* respectively (Huijbregts et al. 2016), let's say 20 kg of both substances are identified in the inventory phase, to translate this to CO_2-equivalent both have to multiplied by their CF. Leading to a total summed up quantity of 1700 *kg CO_2-eq* for these two substances (1680 + 20).

Including the impact on biodiversity in LCIA has developed a lot during the last 20 years (Winter et al. 2018). Currently three of the five human impacts have been incorporated in LCIA, being: habitat change due to land change or water use, climate change due to carbon dioxide emissions and pollution due to e.g. pH change or nutrient load change (Winter et al. 2017). These are, for example, covered in the LCIA method ReCiPe (Goedkoop et al. 2009; Huijbregts et al. 2016). The incorporation of land use in LCIA has received a lot of attention for example with the UN Environment (Teixeira et al. 2016; Verones et al. 2017).

There are many different ways of assessing the impact of land use on biodiversity through LCIA (Michelsen and Lindner 2015; Winter et al. 2017). Currently, the most popular method for assessing biodiversity uses CFs based on the species richness of an area (de Souza et al. 2015; Michelsen and Lindner 2015). Species richness is simply taken as the count of species of an ecological community (Gotelli, N. J., & Colwell 2011). However, by simply calculating the biodiversity of an area based on its species richness, the function a species can have in the ecosystem is not taken into account. For example, while an ecosystem can have many species, their functions might overlap, e.g.: if multiple trees have the same canopy height these trees can be considered to have the same function in this regard; if one species would disappear the niche remains occupied by other species of the same height and the niche regarding canopy height will not have changed. Thus, depending on which species reside in an ecosystem, not all species are of equal importance for the functioning of an ecosystem, something which is assumed in species richness (Mouchet et al. 2010). It is argued that classifying biodiversity through functional diversity (FD) better represents ecosystem functioning compared to taxonomic measures such as species richness (Díaz and Cabido 2001; Mouchet et al. 2010). FD refers to the components of biodiversity which have an influence on the functioning and reliability of an ecosystem (Tilman 2001; Mason et al. 2005). The distribution of functional units (traits) in a multidimensional space is used to determine the biodiversity in an area (Villéger et al. 2008; Mouchet et al. 2010).

There are many different ways to calculate and quantify FD (Mouchet et al. 2010; Ahmed et al. 2018). Mason et al. (2005) argue for describing FD using multiple indices, as using only a single metric will not represent all different aspects of FD and can result in a loss of information (Ahmed et al. 2018). It has been suggested to describe FD using three independent and complementary indices namely, functional richness (FRic), functional evenness (FEve) and functional divergence (FDiv) (Mason et al. 2005; Villéger et al. 2008).

These three FD indices all represent a different aspect of FD. FRic represents the total amount of functional space filled by the community (Figure 1A). A low FRic indicates that some of the resources of a community are unused (Mason et al. 2005). When using multiple traits, FRic is calculated by taking the volume of a convex hull representing the trait values of all present species occurring in the community studied (Villéger et al. 2008). FEve represents the distribution of species abundance in the functional trait space (Figure 1B). Low FEve means a low utilisation of the total available trait space which could lead to decreased productivity (Mason et al. 2005). FDiv tells something about how the abundance of species is distributed inside the utilised volume of the trait space (Villéger et al. 2008; Figure 1C). Low FDiv indicates that abundant species have trait values close to each other, meaning low niche differentiation (Mason et al. 2005). These three indices together provide a more complete view of functional diversity as a whole, by describing the different aspects of FD (Villéger et al. 2008).

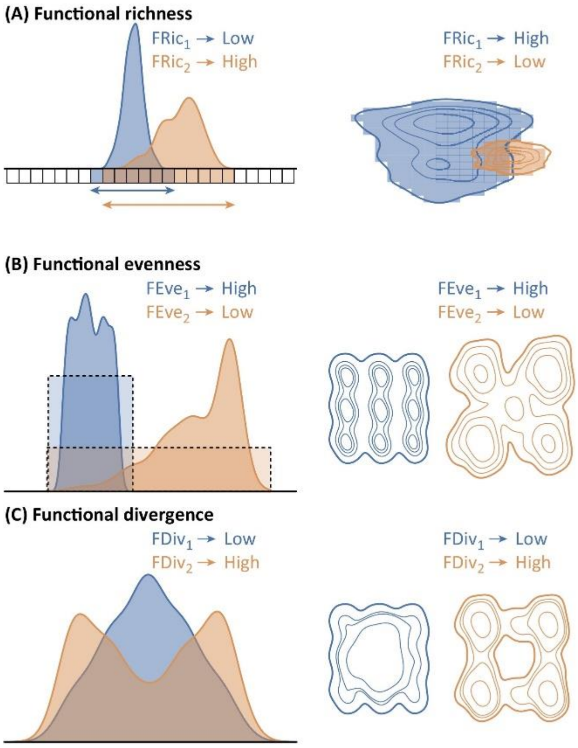

Figure 1. Graphic illustration of the differences between high and low values for the functional diversity indices (a) functional richness, (b) functional evenness, (c) functional divergence. (From: (Carmona et al. 2016))

Currently, there is only one case where FD is implemented for usage in LCIA, which is done by de Souza et al. (2013). De Souza and her colleagues calculated CFs based on FD for different geographic locations spread over the whole American continent. For calculating FD they used Petchey and Gaston's index of FD (Petchey and Gaston 2002) and they included mammals, birds and plants. The method used by de Souza for calculating FD resulted in a single index representing FD based on the total branch length of a functional dendrogram. This method does not take into account any other characteristics of FD mentioned above, meaning it may underestimate the impact on biodiversity. Additionally the method includes mammals and birds besides plants, giving rise to the question whether the method can be applied globally, since information on all these families is not always available.

Therefore, it can be valuable to create a method for the development of CFs based on multiple FD indices to assess the impact of land use on biodiversity. In this study I propose a new method for calculating CFs, based on multiple the FD indices FRic, FEve and FDiv, for assessing impact of land use on plant biodiversity. This method is applicable for multiple geographical regions and various data sources. Publicly available plant abundance, trait data, land use data and environmental data from Germany were used to demonstrate the applicability of the method.

2. Method

To calculate CFs (section 2.1.), FD was determined for reference and occupation land use types in Germany (section 2.2.). To calculate FD, abundance and trait data was used (section 2.3.). Land use data was needed to identify the land use type of the plots (area of land with vegetation) present in the abundance data (section 2.4.). To exclude other confounding variables potentially influencing FD, plots of reference and occupation land uses types were matched based on covariates before calculating CFs (section 2.5.). All described data came from different sources, to get these sources compatible with each other and perform the calculations, multiple data preparation steps were needed (Figure 2).

2.1. Characterisation factors

CFs were calculated by taking the relative difference in biodiversity quality between a reference state and an occupation state (Koellner et al. 2013). In this study, the reference states were the natural land use types and the occupation states were the anthropogenic land use types. The difference in biological diversity, ΔQ expressed in units of potentially disappeared fraction of functional diversity (PDF_{FD}), was calculated using the relative loss in FD between treatment and control land use. The following equation (1) followed where FD_{occ} is the FD in the occupation or treatment land use, FD_{ref} is the FD for the reference or control land use. Median values of the control and treatment FD indices were taken as input.

$$\Delta Q = 1 - \frac{FD_{occ}}{FD_{ref}} \tag{1}$$

For every FD index the CF was calculated, this resulted in three CFs for the three FD indices. The CF representing the impact of land use due to human activities, was expressed in units of $PDF_{FD} \cdot m^2 \cdot a \cdot m^{-2}$, equation (2). Where A represented the area (m^2) of occupation and t the time (year) of occupation which was assumed to be 1 year.

$$CF = \frac{\Delta Q \cdot A \cdot t}{A} \tag{2}$$

This resulted in positive and negative values of which positive values indicate a decline in the FD index and negative values indicate an increase in the FD index.

The occupation impact (OI), expressed in units of $PDF_{FD} \cdot m^2 \cdot a$, in LCIA can then be calculated as shown in equation (3).

$$OI = CF \cdot A \tag{3}$$

Equation (3) can also be written as shown in equation (4).

$$OI = \Delta Q \cdot A \cdot t \tag{4}$$

2.2. Functional diversity

FD was calculated using the range and values of plant traits present in a certain area (Villéger et al. 2008). To know which traits are present and what the values are, plant trait and abundance data was used. Plant data was used due to data availability. With this data the three FD indices proposed by Villéger, Mason, & Mouillot (2008) which are: FRic, FEve and FDiv were calculated. This method was chosen because it can calculate the FD indices using multiple traits compared to the method from Mason et al. (2005) which works with one trait.

All traits values were standardised to mean 0 and unit variance before FD calculations. Only plots with species count higher than 3 were used. FD indices were calculated using the "FD" package in R (Legendre and Laliberté 2010). This package used principal coordinate analysis (PCoA) to calculate the three FD indices (Legendre and Laliberté 2010). PCoA was used to construct the dissimilarity matrix for calculating the FD indices, it has as advantage that it avoids the effects of trait-trait correlation. In addition it reduces the dimensionality of the data leading to shorter calculation times (Legras et al. 2019).

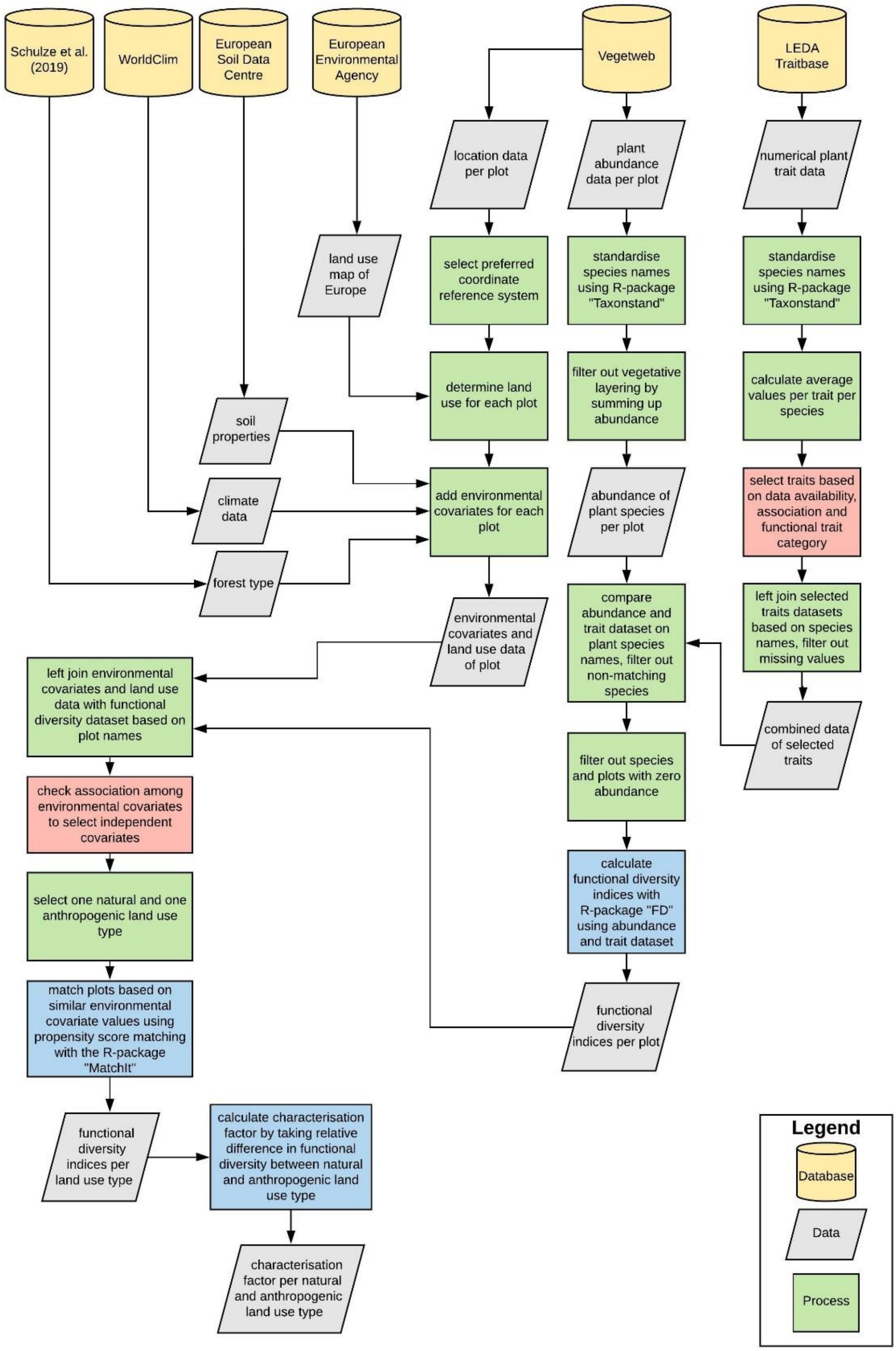

Figure 2. Flowchart showing the method used in this study. Green processes indicate data preparation steps specific to prepare the datasets for implementation in the R-functions mentioned in blue. Red shows steps where a selection was made based on association among variables and blue shows calculation steps. Each plot supplied by Vegetweb had a unique plot name. One coordinate reference system present in the location data was not usable and removed. Vegetative layering present in abundance data made a distinction between different canopy layers resulting in the same species appearing multiple times, this was taken out by summing up the abundance of all layers per species. Functional diversity indices used were functional richness, functional evenness and functional divergence.

2.3. Abundance and trait data

Vegetation abundance data was taken from the German Vegetweb (Jansen et al. 2015). The full dataset of Vegetweb spans from 1922 to 2017, contains 125747 plots at the moment of writing and shows abundance for all present plant species in a plot. For the scope of this study only free data ranging from 1998 to 2017 was used, resulting in a subset containing 5215 plots scattered all over Germany (see figure A1 in the appendix). Abundance data was given per vegetation layer in mean cover percentage for 1684 unique plant species, e.g. tree saplings and adults trees were reported individually as they occur in different vegetation layers. The layering per vegetation layer was removed by summing up the abundance of all layers per species per plot. Median of plot area was 15 m^2, most frequent plot area was 4 m^2. Plots with an area above 100 m^2 were removed from the dataset, as plot area can have an effect on FD (Wang et al. 2013). For 11.8% of the data the area was unknown and assumed to be below 100 m^2.

Trait data was taken from the LEDA Traitbase (Kleyer et al. 2008). LEDA is an open internet database containing life-history traits for the Northwest European flora. Four traits of the total 26 available traits available were selected for the calculation of FD, the selected traits were: specific leaf area, canopy height, seed number and seed mass. present in the data In the database every trait had a different number and combination of species present, this ranged from 1646 to 2805 species. For many species, multiple values were given per trait. The arithmetic mean was taken of those values so a single value per trait per species was left. All plant names present in the trait and abundance dataset were standardised using the "Taxonstand" package in R (Cayuela et al. 2012).

For plant trait selection the following decision factors were taken into account: trait functional category, association among traits and species coverage per trait. Plant traits can fall into three functional categories being: persistence, regeneration and dispersibility (Kleyer et al. 2008). Of every functional category at least one trait was selected. Only numeric traits were chosen for further calculations. Categorical traits were not used because these increased the number of the PCoA axis a lot, increasing the loss of information during FD calculations. This did not happen when only using numeric traits. Trait values can covary among each other so Spearman correlation was calculated for all numeric traits in the LEDA Traitbase.

The following traits were selected: specific leaf area, canopy height, seed number and seed mass (see full correlation matrix in table A2 in the appendix). Specific leaf area is a key trait explaining different ecological strategies within communities (Funk et al. 2017). It shows persistence of plants species and hardly correlates with other traits. Canopy height also shows persistence of a plant. It correlates with many traits present in the database making it a good trait to represent those. Seed number is a trait important for regeneration. It does not correlate much with other traits thus shows a different aspect of the trait spectrum. Seed mass is also related to regeneration and does not correlate much with the other selected traits. Significant correlations coefficients of selected traits ranged from -0.296 to 0.371 among each other, only seed mass and leaf area was non-significant.

The functional trait group dispersibility is not present in the four selected traits. The functional category dispersibility is present in the initial dataset by seed release height. This correlated significantly with canopy height and was not chosen for this reason. In addition canopy height contained 2805 plant species compared to 2524 for seed release height, increasing the change of matching species between the different traits and in the end with the abundance dataset. After trait selection, the selected traits values were combined and all missing values were taken out, this resulted in trait data being available for 1257 plant species.

The dataset containing the trait values and the dataset containing the abundance data were matched against each other based on plant species. This resulted in 860 plant species occurring in both datasets. Plots with zero abundance were removed. The occurrence dataset contained 5050 plots of the initial 5215. For on average 76% of the species in the abundance dataset, trait values were known. The percentage of traits covered of the total abundance of species can have a confounding influence on FRic and was later on used to account for confounding variables.

2.4. Land use and environmental data

Land use data was taken from the CORINE Land Cover (CLC) map of the Copernicus land monitoring service which covers western and central European countries (European Environmental Agency 2000). Land use maps were available for the years 1990, 2000, 2006, 2012 and 2018. It has a minimal mapping unit of 25 ha for areal phenomena and 100 m for linear phenomena. It contains an inventory of land cover in 44 classes. The date the vegetation data was collected was used to match the CLC map closest to that year. Plots from the years 1998 through 2002 were matched with the CLC map of 2000, plots from the years 2003 through 2008 were matched with the CLC map of 2006, plots from the years 2009 through 2014 were matched with the CLC map of 2012 and plots from the year 2017 were matched with the CLC map of 2018. The years 2015 and 2016 were not present in the plot data. Location data from the plots was supplied in three forms, two different coordinate reference systems and an old German topographic map collection "*Messtischblatt*". Only location data given in the two coordinate reference systems were used, as the map collection data was unprecise. This resulted in 4007 (of the 5215) plots for which precise location data was available.

For forests it was classified whether or not it was natural using data from Schulze et al. (2019). They classify four types of forest classes namely: primary, naturally regrown, planted and unclassified. All forests marked as planted were removed from the forest land use types. Forests marked in any other class were left in the dataset.

Six land use types were chosen to continue calculations with, three natural land uses and three anthropogenic types. The chosen land use types were: broad-leaved forest, coniferous forest, mixed forest, non-irrigated arable land, pastures and complex cultivation patterns. These land use types were chosen because these had the most available datapoints, increasing the chance of success of propensity score matching (PSM) later on (see table A3 in the appendix). Another reason why these land uses were chose is because Europe would consist of 80-90% forest without human intervention (Rosenzweig 1995), in Germany specifically deciduous (i.e. broad leaved) and mixed forest would dominate (Federal Agency for Nature Conservation 2015). The land use type "Land principally occupied by agriculture, with significant areas of natural vegetation" was not chosen because it could both by seen as a natural and anthropogenic land use type.

Additional environmental variables were added, besides land use. These variables were used to account for confounding influences using PSM (section 2.5). The extra variables were: annual mean temperature, temperature seasonality, maximum temperature of warmest month, minimum temperature of coldest month, annual precipitation, precipitation in wettest month, precipitation in driest month, precipitation seasonality. These variables all came from the WorldClim – Global Climate Data version 2.0 raster data at resolution 30 seconds (approximately 1 km^2) (Fick and Hijmans 2017). Next to this also soil properties were added being: organic carbon, pH, clay content, sand content, silt content, bulk density and available water capacity. This data was taken from the European Soil Data Centre (ESDAC) and had a resolution of 500 m. (Panagos et al. 2012; de Brogniez et al. 2015; Ballabio et al. 2016).

2.5. Propensity score matching

To be able to calculate the relative difference in FD between a reference and occupation land use, plots needed to score similarly in covariates. This way external environmental factors are more controlled and land use is the only explanatory variable. So only plots which have approximately the same environmental variables can be compared to each other. In order to rule out other covariates having an influence on FD other than land use, PSM was used (Olmos and Govindasamy 2015). PSM tries to account for the covariates which might have an influence on the treatment outcome. PSM calculates a propensity score for available covariates and matches control and treatment groups which have scores close to each other (Olmos and Govindasamy 2015). By doing this it makes an attempt at reducing the bias these covariates might have on the treatment group, as only the land uses differ. To conduct the

PSM, the dataset containing the FD values and the dataset containing land use were merged. After all data handling steps, a total of 2197 plots were left for PSM and CF calculations.
Before and after PSM the standardised difference of the covariates was calculated in percentages (Olmos and Govindasamy 2015). It was calculated by taking the difference in average of the covariates between control and treatment, scaled by the square root of the sum of the variances (Imbens and Wooldridge 2009). The standardised difference shows the imbalance between the covariates, as imbalance goes down the values of the covariates are closer to each other for the control and treatment group. Covariate imbalance should generally decline and is desired to be below 25% after matching (Stuart, Elizabeth A and Rubin 2008). Due to the matching of the propensity scores the imbalance between the covariates should become lower than before matching.

Selection of covariates for usage in PSM was done as follows: spearman correlation was calculated for all pairs of environmental variables. Covariates which correlated most with FD (mean of FD indices) and correlated least with each other were selected (Cuong 2013; Tanner-Smith and Lipsey 2014). Using the selection criteria mentioned the following environmental covariates were selected: annual precipitation, sand content and minimum temperature. In addition, the ratio of species for which traits were know of the total species present in a plot was also used as a metric for PSM. The absolute correlation coefficients between covariates ranged from 0.117 to 0.335 (see table A4 in the appendix for full correlation matrix).

During matching natural land uses were used as control group. Anthropogenic land uses were used as treatment group. The land use types used as control were: broad-leaved forest, coniferous forest and mixed forest. These were all matched against the treatment land use types: non irrigated arable land, pastures and complex cultivation patterns. This resulted in nine matching pairs of which for all FD indices a CF was calculated. So for all nine matching pairs different datapoints can be selected for pairing land use types, e.g. the plots chosen when broad leaved forest and pastures get matched can differ from the ones that get matched between broad leaved forest and complex cultivation pattern.

PSM was done using the following method: nearest neighbour matching with a caliper of 0.25, with matching order starting at the largest propensity scores and discarding plots from both control and treatment group (Lunt 2014; Olmos and Govindasamy 2015).

Nearest neighbour matching was used, as this has the same results as full matching but requires less calculation time (Austin 2014). Largest to lowest matching order led to lower imbalance between covariates after matching compared to matching order lowest to largest. Plots were discarding from both groups because not all control and treatment groups had the same amount of plots for all to be matched. Cases were discarded if they fell outside the support of the distance measure, here a logistic measure, meaning when no other match could be found plots from either control or the treatment group were discarded. The caliper specifies the maximum difference allowed between matched propensity scores (Lunt 2014). A range of different calipers was tested ranging from 0.1 to 0.5 with steps of 0.05, this all resulted in non-significant difference in the results. Only the imbalance after matching increased, meaning less precise matching which is undesired. Above mentioned matching method resulted in the lowest imbalance between covariables after matching which is leading in all decisions regarding PSM (Lunt 2014). PSM was done using the R package “MatchIt” (Ho et al. 2011).

After PSM the FD indices of the groups were compared using a non-parametric paired Wilcoxon signed-rank test due to non-normal distribution of FD indices data. This was done to statistically test whether the control and treatment group differed from each other. The null hypothesis is that the medians of the control and treatment group are the same. A significance level of $\alpha = 0.05$ is assumed.

3. Results

3.1. Functional diversity

Broad leaved forest versus all anthropogenic land uses show a significant difference in FD indices (Figure 3A, 3B and 4A and table A5 of the appendix).

Coniferous forest versus non-irrigated arable land show significant differences for all FD indices (Figure 4B and A5 of the appendix). Coniferous forest versus complex cultivation patterns show significant differences for two FD indices except FDiv (Figure 5A and A5 of the appendix). Coniferous forest versus pastures show no significant difference between FD indices (Figure 5B and A5 of the appendix).

Mixed forest versus no-irrigated arable land only show significant difference for FDiv (Figure 6A and A5 of the appendix). Mixed forest versus pastures show significant differences for the FD indices except FEve (Figure 6B and A5 of the appendix). Mixed forest versus complex cultivation patterns show significant differences for all FD indices (Figure 7 and A5 of the appendix).

When looking at the imbalance of the covariates before and after PSM (table A6 of the appendix) it can be seen that imbalance of the covariates decreased after the matching (i.e. spread of covariate values decreased). For every land use pair new plots were matched (table A7 and A8 of the appendix) and others were discarded when propensity score were diverging too much. Many high and low propensity scores were unmatched or discarded, letting only scores with nearest scores match (figure A9 up to and including A17 of the appendix)

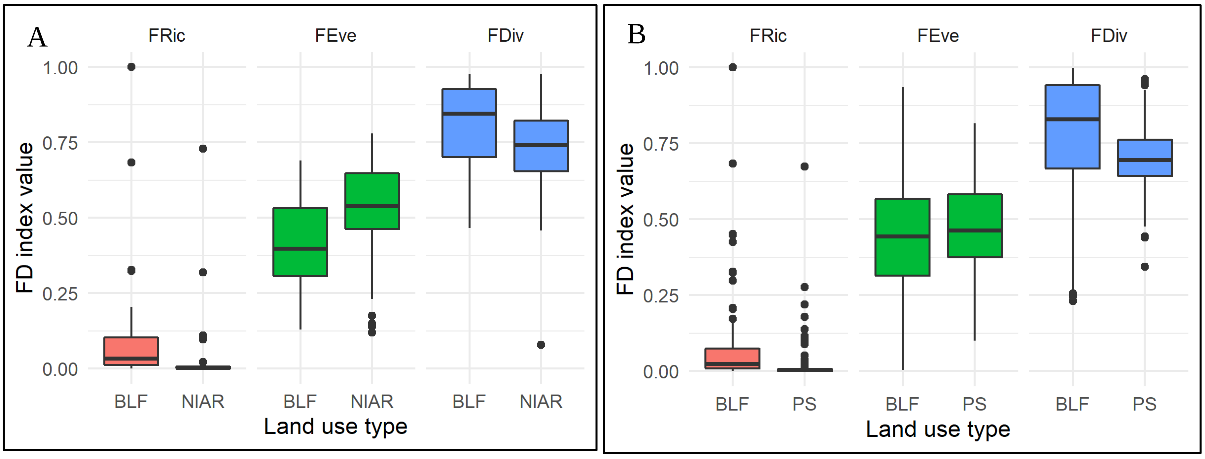

Figure 3. Boxplots of the three functional diversity indices functional richness (FRic), functional evenness (FEve) and functional divergence (FDiv). The natural land use broad leaved forest (BLF) is shown versus the anthropogenic land uses non-irrigated arable land (NIAR) and pastures (PS) in respectively A and B.

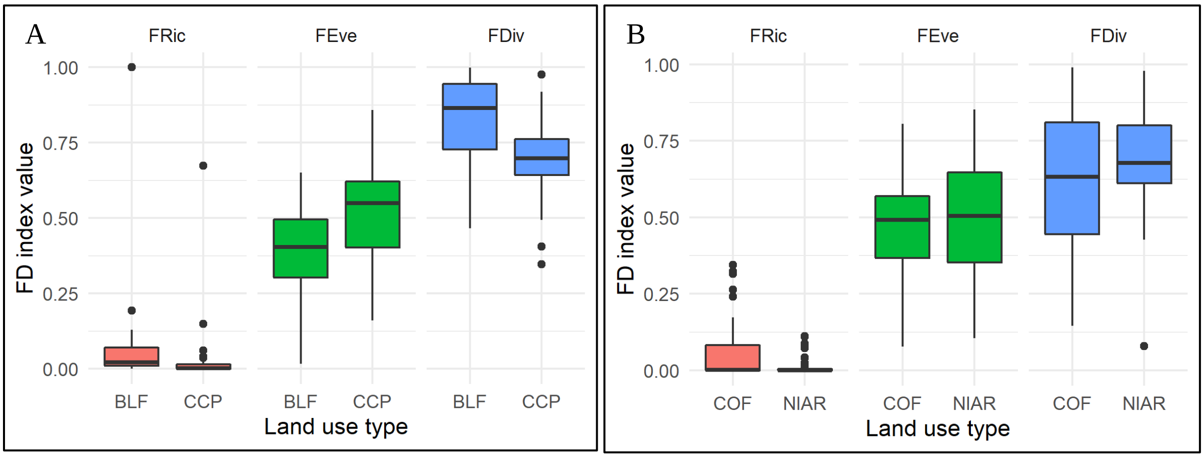

Figure 4. Boxplots of the three functional diversity indices functional richness (FRic), functional evenness (FEve) and functional divergence (FDiv). The natural land uses broad leaved forest (BLF) and coniferous forest (COF) are shown versus the anthropogenic land uses, non-irrigated arable land (NIAR) and complex cultivation patterns (CCP) in respectively A and B.

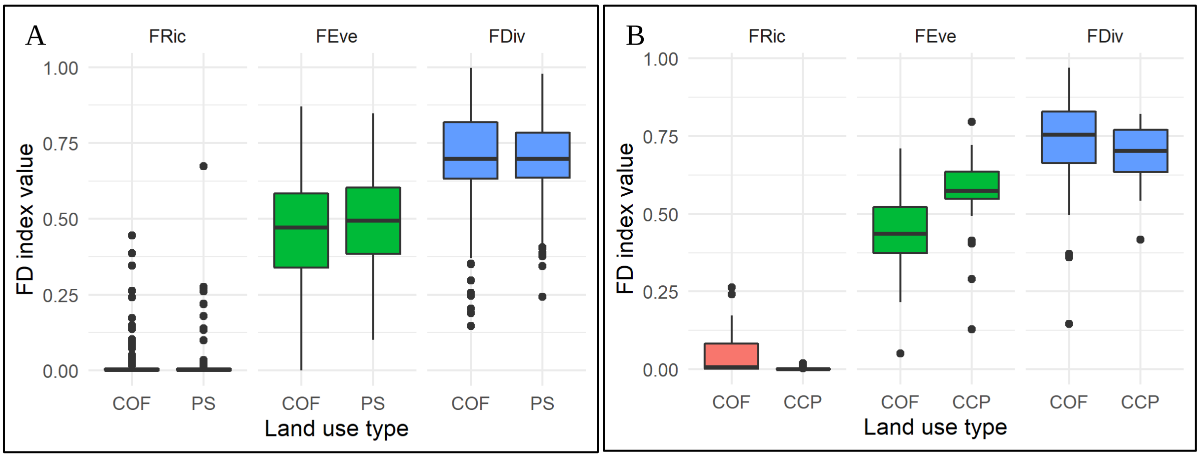

Figure 5. Boxplots of the three functional diversity indices functional richness (FRic), functional evenness (FEve) and functional divergence (FDiv). The natural land use coniferous forest (COF) is shown versus the anthropogenic land uses, pastures (PC) and complex cultivation patterns (CCP) in respectively A and B.

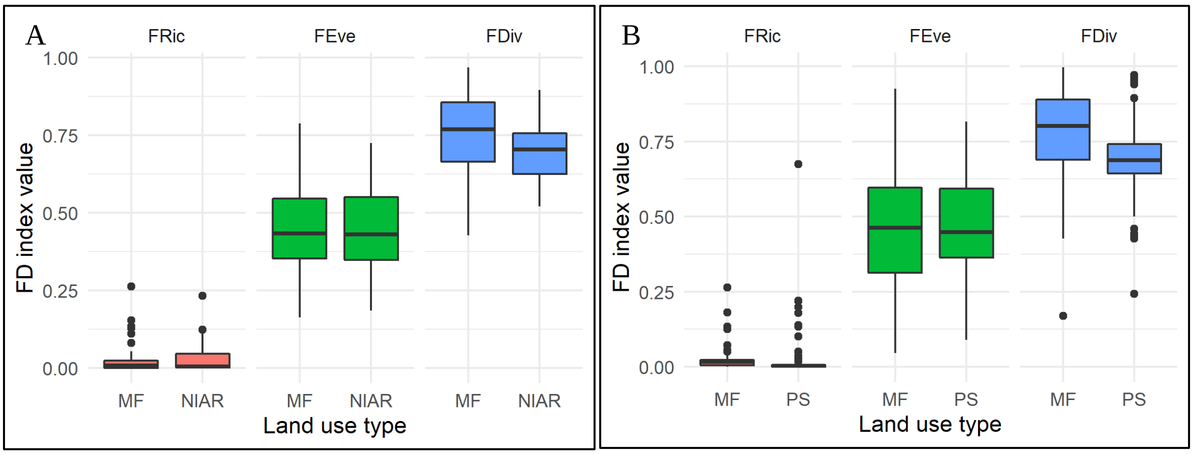

Figure 6. Boxplots of the three functional diversity indices functional richness (FRic), functional evenness (FEve) and functional divergence (FDiv). The natural land use mixed forest (MF) is shown versus the anthropogenic land uses, non-irrigated arable land (NIAR) and pastures (PS) in respectively A and B.

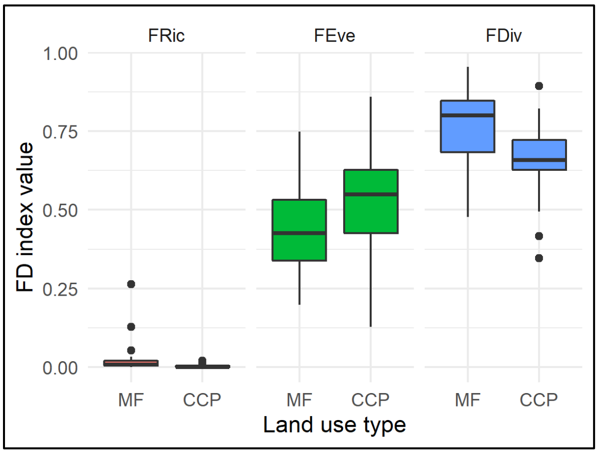

Figure 7. Boxplots of the three functional diversity indices functional richness (FRic), functional evenness (FEve) and functional divergence (FDiv). The natural land uses mixed forest (MF) versus anthropogenic land use complex cultivation patterns (CCP) are shown.

3.2. Characterisation factors

CFs were calculated according to equation (2) and are shown in Table 1. The CFs have been calculated for all natural land uses versus anthropogenic land uses including non-significant ones.

Table 1. Characterization factors (CF) expressed in $PDF_{FD} \cdot m^2 \cdot a \cdot m^{-2}$ for all functional diversity (FD) indices for different reference and occupation land use types. Significance codes of paired Wilcoxon signed rank test of the FD values used to calculate the CFs are the following: "#" = not significant, "" = p-value <0.1, "**" = p-value <0.05.*

REFERENCE LAND USE	OCCUPATION LAND USE	CF_{FRIC}	CF_{FEVE}	CF_{FDIV}
BROAD LEAVED FOREST	Non-irrigated arable land	0.922**	-0.359**	0.123**
	Pastures	0.823**	-0.045**	0.163**
	Complex cultivation patterns	0.946**	-0.358**	0.192**
CONIFEROUS FOREST	Non-irrigated arable land	0.560**	-0.025#	-0.072**
	Pastures	-0.090#	-0.050#	0.001#
	Complex cultivation patterns	0.884**	-0.316**	0.071#
MIXED FOREST	Non-irrigated arable land	0.458#	0.004#	0.084*
	Pastures	0.766**	0.031#	0.143**
	Complex cultivation patterns	0.907**	-0.287**	0.178**

Almost all CFs for FRic show a significant decline in FRic for the occupation land use compared to the reference land use. The significant CFs ranged from 0.560 to 0.946 $PDF_{FD} \cdot m^2 \cdot a \cdot m^{-2}$. Two insignificant CFs were found for coniferous forest versus pastures and mixed forest versus non-irrigated arable land.

All significant CFs for FEve show an increase in FEve for anthropogenic land use compared to the reference land use. The significant CFs for FEve ranged from -0.358 to -0.045 $PDF_{FD} \cdot m^2 \cdot a \cdot m^{-2}$. The non-significant CFs for FEve were for coniferous forest and mixed forest both compared to non-irrigated arable land and pastures.

Almost all CFs for FDiv show a decline in FDiv for the occupation land use compared to the reference land use. The significant CFs show a range from -0.072 to 0.192 $PDF_{FD} \cdot m^2 \cdot a \cdot m^{-2}$. The only significant one going against the trend of having an decline in FDiv is coniferous forest versus non-irrigated arable land which has a positive increase in FDiv. Two insignificant CFs for FDiv were found for coniferous forest versus pastures and complex cultivation patterns.

Broad leaved forest as reference land use versus all the anthropogenic land uses showed the biggest negative impact on FD.

4. Discussion

In this study, a method has been developed to calculate CFs to evaluate the impact of different land uses on biodiversity in Germany, based on FD as defined by Villéger et al. (2008). The CFs all show the same trend: a decrease in FRic, increase in FEve and decrease in FDiv for anthropogenic land use types. The increase in FEve can be explained by the fact that both FRic and FDiv decrease, meaning there are less traits present which are closer to each other. FEve tells us that the functional trait space is more utilised, which means, when looking at Figure 1 and taking into account the decrease of FRic and FDiv, there is less space to be filled indicating it is easier for FEve to increase. After PSM, there was a general decline in imbalance of the covariate values, indicating that covariates were not responsible for the difference in biodiversity.

Although the CFs show the same trend for all the FD indices, the difference in values show the influence the reference state can have on the CF. This difference shows the importance of correct reference state selection (Chiarucci et al. 2010). This also stresses the importance of geographic differentiation among CFs, every geographic location where land use occupation occurs can have a different reference state. Occupation land use types can also have a different impact at another location, as crops are for example grown in different intensities in different locations. So, the same land use might have a different impact on a different place on earth (Koellner et al. 2013).

The CFs in this study are able to distinguish different levels of impact among anthropogenic occupation land use types. Complex cultivation patterns has the largest negative impact on biodiversity, revealing the difference in impact the anthropogenic land uses can have on biodiversity.

When comparing the CFs in other studies with this study, the main difference is the way the CF was calculated, by using species richness instead of FD. Species richness is another way of looking at biodiversity, making it more difficult to compare the CFs from this study to other studies. But the overall trend of having a decrease in biodiversity for anthropogenic land uses is present in both this study and other studies (De Baan et al. 2013; Knudsen et al. 2017). Even though the CFs show a decrease in biodiversity, CF based on species richness and FD show a different aspect of biodiversity. Hence, not one way should be used, they can both add to each other and give LCA practitioners a more detailed view of what really is the impact of a certain land use on biodiversity.

This study has shown that the method described can produce significant CFs in line with trends shown in other studies. This opens the way for the development of CFs for other geographic locations and land uses using FD. Although this study focused on Germany, the method can be applied to every geographic location of which plant occurrence, traits data and land use is known.

In future research this method can be used to expand the geographical and land use type coverage of CFs by using other databases. For example, for traits the "TRY" database can be used, for abundance data the worldwide plant community data repository "sPlot" (Bruelheide et al. 2019) and its European counterpart the "European Vegetation Archive" (EVA) (Chytrý et al. 2016).

In this study, plant species were used. There is the belief plants might correlate well with other species (Köllner 2000; Vogtländer et al. 2004) but it is also being questioned whether one well-studied species group can represent a whole ecosystem correctly (Purvis and Hector 2000). Nonetheless, forests, as used in this study, are more likely to be biodiversity hotspots, being the home to the highest diversity for many taxonomic groups increasing the importance forests have for general biodiversity conservation (Lindenmayer et al. 2006). This last statement and the big availability of plant data makes it an ideal taxonomic group for biodiversity research.

Multiple data sources on abundance, traits, land use and environmental data were combined in this study. All these data sources have their own uncertainties and variations, summarizing data involves considering all these factors (Gurevitch and Hedges 1999). It was beyond the scope of this study to do a full statistical meta-analysis on these uncertainties.

LCA has become an important tool to assess the impact product systems have on the environment. It helps policy makers and producers make important decisions in setting up policy and making new products (Hellweg and Mila i Canals 2014). By improving and developing the method of LCA it becomes more and more detailed leading to policies and products of which is known what the impact is on the environment. This gives society the tools to strive and work towards a more sustainable future. This is also at the core of Industrial Ecology, to help shape a more sustainable future using natural, engineering and social sciences (Ehrenfeld 2004; Ghisellini et al. 2016). LCA and the development of its method is at the heart of Industrial Ecology (Ehrenfeld 2004).

5. Conclusions

This study aimed to create a method for the development of CFs based on the FD indices FRic, FEve and FDiv to asses the impact of land use on biodiversity. By using data from Germany the method was demonstrated and resulted in significant CFs in line with other studies by showing a decline in biodiversity for anthropogenic land uses. The developed method can lead the way to making a geographically more precise assessment of the impact land use has on biodiversity in certain regions. In addition, by looking at biodiversity from an FD perspective it can add to the current practice of using species richness to asses biodiversity. Thus, giving LCA practitioners a more detailed view of what the impact is of a certain land use type on biodiversity.

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7. Appendix

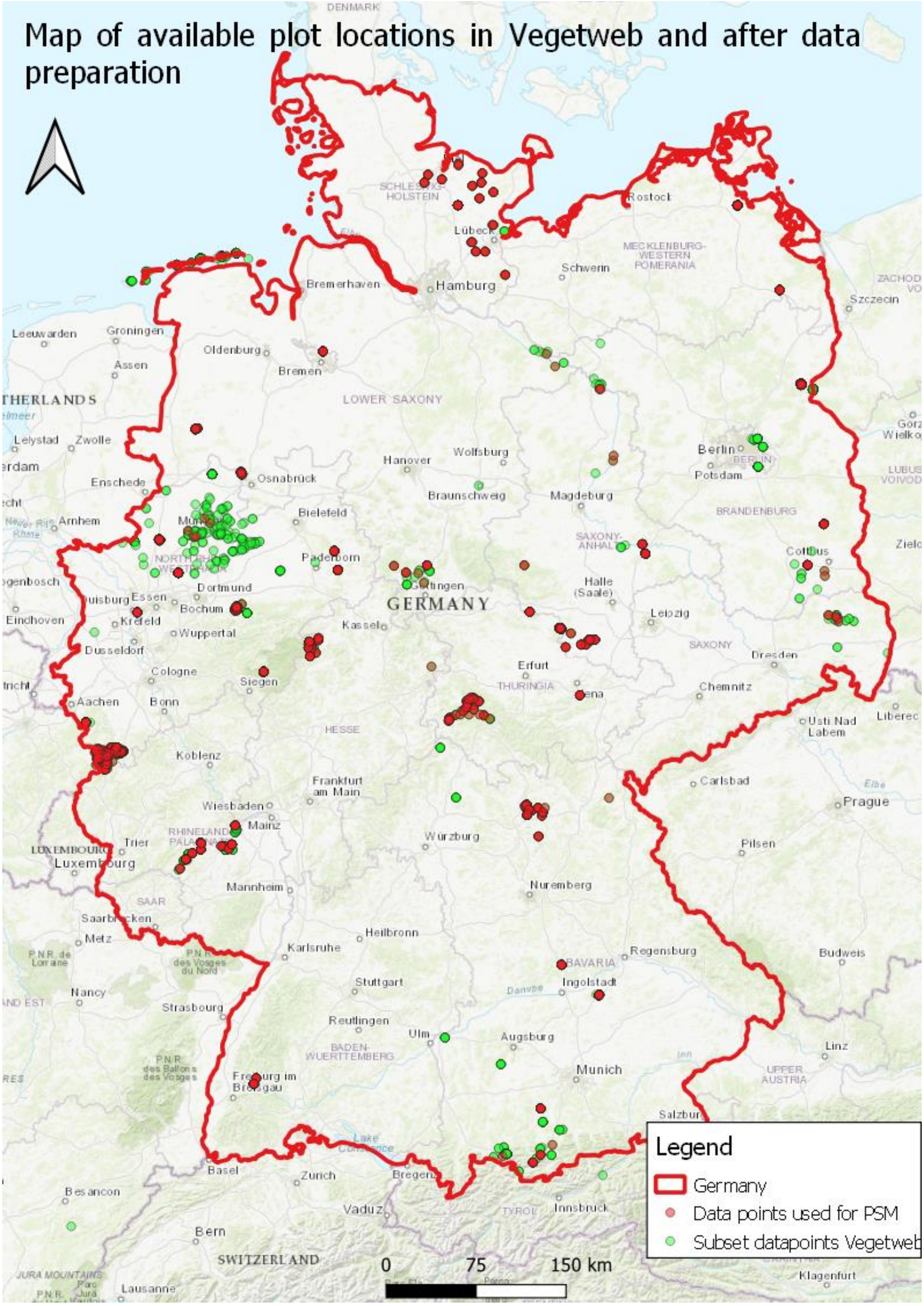

Figure A1. Map of all available datapoint present in subset Vegetweb dataset used and the ones used after data preparation for usage in propensity score matching (PSM).

Table A2. Spearman correlation of plant traits. Bold traits and values belong to selected traits used for FD calculations. Lower left half of the table represents the correlation coefficient r of the spearman correlation test. Upper right half shows the p-values of the correlation test.

	canopy height	leaf dry mass	**leaf area**	leaf mass	leaf size	seed release height	**seed mass**	**seed number**	seed number per shoot
canopy height		0.033	**0.047**	0.000	0.000	0.000	**0.000**	**0.000**	0.000
leaf dry mass	0.065		0.000	0.245	0.000	0.004	0.748	0.019	0.003
leaf area	**-0.060**	-0.488		0.000	0.010	0.009	**0.949**	**0.020**	0.020
leaf mass	0.627	-0.035	-0.130		0.000	0.000	0.000	0.000	0.000
leaf size	0.624	-0.154	0.078	0.959		0.000	0.000	0.000	0.000
seed release height	0.910	0.087	-0.078	0.659	0.652		0.000	0.000	0.000
seed mass	**0.371**	0.010	**-0.002**	0.414	0.418	0.334		**0.000**	0.000
seed number	**0.201**	-0.071	**0.070**	0.140	0.163	0.214	**-0.296**		0.000
seed number per shoot	0.211	-0.090	0.070	0.139	0.162	0.220	-0.312	0.984	

Table A3. Number of datapoints shows per land use type after data handling. Bold entries are used for calculation of characterisation factors.

number	**Land use type**
16	Discontinuous urban fabric
73	Mineral extraction sites
1	Sport and leisure facilities
682	**Non-irrigated arable land**
22	Vineyards
582	**Pastures**
66	**Complex cultivation patterns**
113	Land principally occupied by agriculture, with significant areas of natural vegetation
318	**Broad-leaved forest**
386	**Coniferous forest**
208	**Mixed forest**
1	Natural grasslands
25	Transitional woodland-shrub
15	Inland marshes
4	Peat bogs
35	Water courses
9	Water bodies

Table A4. Spearman correlation of covariates before propensity score matching. MeanFD is mean correlation of the three FD indices with the environmental variable. Functional richness (FRic), functional evenness (FEve), functional divergence (FDiv), ratio is the ratio of species for which traits were know of the total species present in a plot, mean annual temperature (meanT), temperature seasonality (seasT), max temperature of warmest month (maxT), minimal temperature of coldest month (minT), total annual precipitation (totalP), precipitation in wettest month (maxP), precipitation in driest month (minP), precipitation seasonality (seasP), soil organic carbon (SOC), pH, clay content (clay), sand content (sand), silt content (silt), bulk density (bulk) and available water capacity (AWC). Lower left half of the table represents the correlation coefficient r of the spearman correlation test. Upper right half shows the p-values of the correlation test.

	Mean FD	FRic	FEve	FDiv	**ratio**	mean T	Tseas	maxT	**minT**	**totalp**	maxp	minp	pseas	SOC	pH	clay	**sand**	silt	bulk	AWC
FRic	0.527		0.000	0.292	0.000	0.633	0.632	0.083	0.666	0.000	0.000	0.000	0.000	0.943	0.302	0.000	0.000	0.000	0.173	0.000
FEve	0.545	-0.460		0.000	0.489	0.000	0.000	0.000	0.262	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000
FDiv	0.432	0.119	-0.176		0.408	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ratio	0.031	-0.030	-0.034	-0.028		0.000	0.009	0.000	**0.000**	**0.003**	0.000	0.021	0.007	0.909	0.000	0.086	**0.000**	0.000	0.054	0.074
mean T	0.133	-0.173	0.131	-0.095	-0.165		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
seasT	0.147	-0.086	0.099	-0.256	0.101	0.062		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.026	0.000	0.000	0.000	0.000
maxT	0.176	-0.147	0.135	-0.246	-0.127	0.772	0.639		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
minT	**0.096**	0.034	-0.062	0.191	**-0.097**	0.291	-0.870	-0.333		**0.000**	0.238	0.000	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000
totalP	**0.242**	0.287	-0.223	0.217	**-0.015**	-0.620	-0.610	-0.767	**0.295**		0.000	0.000	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000
maxP	0.223	0.294	-0.180	0.195	-0.133	-0.625	-0.506	-0.688	0.145	0.934		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
minP	0.243	0.287	-0.213	0.229	-0.025	-0.589	-0.591	-0.735	0.294	0.978	0.910		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
seasP	0.218	-0.245	0.191	-0.217	-0.046	0.291	0.702	0.616	-0.583	-0.712	-0.556	-0.756		0.000	0.000	0.000	0.000	0.000	0.000	0.000
SOC	0.142	0.075	-0.155	0.196	0.018	-0.379	-0.659	-0.672	0.489	0.705	0.603	0.674	-0.615		0.000	0.000	0.000	0.004	0.000	0.000
pH	0.113	-0.152	0.062	-0.124	0.134	0.279	0.563	0.477	-0.377	-0.683	-0.686	-0.712	0.560	-0.513		0.000	0.000	0.000	0.000	0.000
clay	0.181	0.271	-0.115	0.158	0.006	-0.523	-0.031	-0.388	-0.202	0.396	0.475	0.392	-0.201	0.130	-0.275		0.000	0.000	0.000	0.000
sand	**0.198**	-0.330	0.087	-0.178	**0.076**	0.479	0.111	0.402	**0.117**	**-0.359**	-0.484	-0.365	0.259	-0.070	0.248	-0.848		0.000	0.000	0.000
silt	0.195	0.320	-0.078	0.187	-0.120	-0.455	-0.126	-0.386	-0.092	0.337	0.476	0.347	-0.255	0.061	-0.231	0.751	-0.973		0.000	0.000
bulk	0.071	-0.015	0.079	-0.117	-0.035	0.194	0.279	0.314	-0.182	-0.352	-0.336	-0.347	0.330	-0.310	0.236	-0.599	0.349	-0.244		0.000
AWC	0.232	0.324	-0.171	0.200	0.023	-0.624	-0.222	-0.574	-0.059	0.591	0.635	0.586	-0.390	0.327	-0.393	0.930	-0.824	0.747	-0.606	

Table A5. Functional diversity (FD) statistics after propensity score matching. Nine matching pairs used for propensity score matching are shown. The land use types broad leaved forest (BLF), coniferous forest (COF), mixed forest (MF), non-irrigated arable land (NIAR), pastures (PS) and complex cultivation patterns (CCP) are shown. Median and inter quartile range (IQR) are shown for three FD indices: functional richness (FRic), functional evenness (FEve), functional divergence (FDiv). Significance codes of paired Wilcoxon signed rank test of the FD values between matching pairs are shown: "#" = not significant, "" = p-value <0.1, "**" = p-value <0.05. P-values correspond to the FD index above it.*

Matching pair	Land use type	Median FRic	IQR FRic	Median FEve	IQR FEve	Median FDiv	IQR FDiv
1	BLF	0.0322	0.0928	0.3967	0.2250	0.8454	0.2261
	NIAR	0.0025	0.0068	0.5391	0.1846	0.7415	0.1684
p-value		1.02e-07**		1.63e-05**		0.00137**	
2	BLF	0.0233	0.0646	0.4427	0.2533	0.8298	0.2745
	PS	0.0040	0.0058	0.4628	0.2081	0.6947	0.1189
p-value		5.19e-12**		0.0508**		8.17e-05**	
3	BLF	0.0217	0.0599	0.4044	0.1938	0.8643	0.2162
	CCP	0.0012	0.0141	0.5493	0.2184	0.6983	0.1199
p-value		4.52e-06**		0.000921**		0.000179**	
4	COF	0.0022	0.0822	0.4917	0.2025	0.6329	0.3654
	NIAR	0.0010	0.0048	0.5042	0.2933	0.6781	0.1896
p-value		0.00969**		0.303#		0.0266**	
5	COF	0.0023	0.0058	0.4706	0.2444	0.6983	0.1856
	PS	0.0025	0.0063	0.4942	0.2183	0.6975	0.1488
p-value		0.662#		0.199#		0.212#	
6	COF	0.0063	0.0820	0.4363	0.1473	0.7551	0.1664
	CCP	0.0007	0.0015	0.5740	0.0876	0.7017	0.1372
p-value		0.000217**		0.0254**		0.423#	
7	MF	0.0081	0.0224	0.4332	0.1932	0.7694	0.1921
	NIAR	0.0044	0.0455	0.4314	0.2022	0.7050	0.1322
p-value		0.388#		0.920#		0.0588*	
8	MF	0.0161	0.0177	0.4620	0.2822	0.8011	0.1995
	PS	0.0038	0.0062	0.4476	0.2307	0.6867	0.0988
p-value		4.76e-07**		0.294#		1.75e-07**	
9	MF	0.0081	0.0162	0.4264	0.1942	0.7995	0.1631
	CCP	0.0008	0.0042	0.5488	0.2006	0.6474	0.0951
p-value		7.96e-06**		0.0264**		0.0103**	

Table A6. Imbalance of covariates before and after propensity score matching for nine matching pairs. Land use types broad leaved forest (BLF), coniferous forest (COF), mixed forest (MF), non-irrigated arable land (NIAR), pastures (PS) and complex cultivation patterns (CCP) are shown. Imbalance is given in percentage (%).

Land use type	Before or after PSM	Ratio	Total precipitation	Sand	Minimum temperature
BLF vs NIAR	Before	10.2	253	72.6	129
	After	5.13	43.3	28.8	26.7
BLF vs PS	Before	48.5	99.1	164	12.7
	After	22.1	1.58	1.59	15.9
BLF vs CCP	Before	75.6	54.1	37.7	119
	After	36.7	33.0	38.6	11.5
COF vs NIAR	Before	62.9	184	0.73	0.85
	After	15.8	26.0	28.1	20.0
COF vs PS	Before	102	70.8	81.5	92.7
	After	15.17	8.35	7.34	13.8
COF vs CCP	Before	129	26.3	123	3.77
	After	6.14	30.8	16.8	19.9
MF vs NIAR	Before	38.5	327	89.6	31.2
	After	8.57	15.6	22.0	22.8
MF vs PS	Before	4.36	154	192	102
	After	22.4	8.42	5.48	0.93
MF vs CCP	Before	20.2	123	31.8	30.9
	After	13.6	20.3	11.6	26.6

Table A7. Propensity score matching numbers. The land use types broad leaved forest (BLF), coniferous forest (COF), mixed forest (MF), non-irrigated arable land (NIAR), pastures (PS) and complex cultivation patterns (CCP) are shown. Control is the natural land use type: here being BLF, COF and MX. Treatment is the anthropogenic land use type being: NIAR, PS and CCP. "All" is the total availability of data points available for propensity score matching, "matched" is amount of data points matched, "unmatched" and "discarded" are datapoint not being matched.

Land use type		Control	Treatment
BLF vs NIAR	All	306	682
	Matched	74	74
	Unmatched	83	330
	Discarded	149	278
BLF vs PS	All	306	582
	Matched	151	151
	Unmatched	120	394
	Discarded	35	37
BLF vs CCP	All	306	66
	Matched	41	41
	Unmatched	237	14
	Discarded	28	11

COF vs NIAR	All	375	682
	Matched	70	70
	Unmatched	152	234
	Discarded	153	378
COF vs PS	All	375	582
	Matched	193	193
	Unmatched	117	389
	Discarded	65	0
COF vs CCP	All	375	66
	Matched	26	26
	Unmatched	313	25
	Discarded	36	15
MF vs NIAR	All	186	682
	Matched	38	38
	Unmatched	4	299
	Discarded	144	345
MF vs PS	All	186	582
	Matched	128	128
	Unmatched	58	153
	Discarded	0	301
MF vs CCP	All	186	66
	Matched	28	28
	Unmatched	157	23
	Discarded	1	15

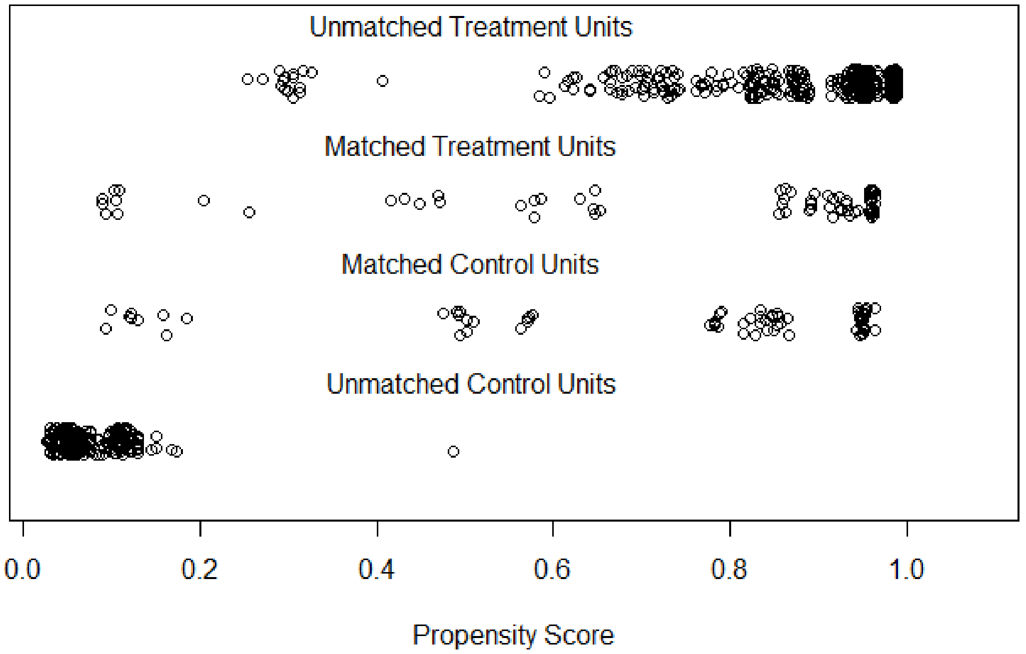

Figure A9. Graphic representation of propensity score matching results for control units being the natural land use: broad leaved forest and treatment units being the anthropogenic land use: non-irrigated arable land.

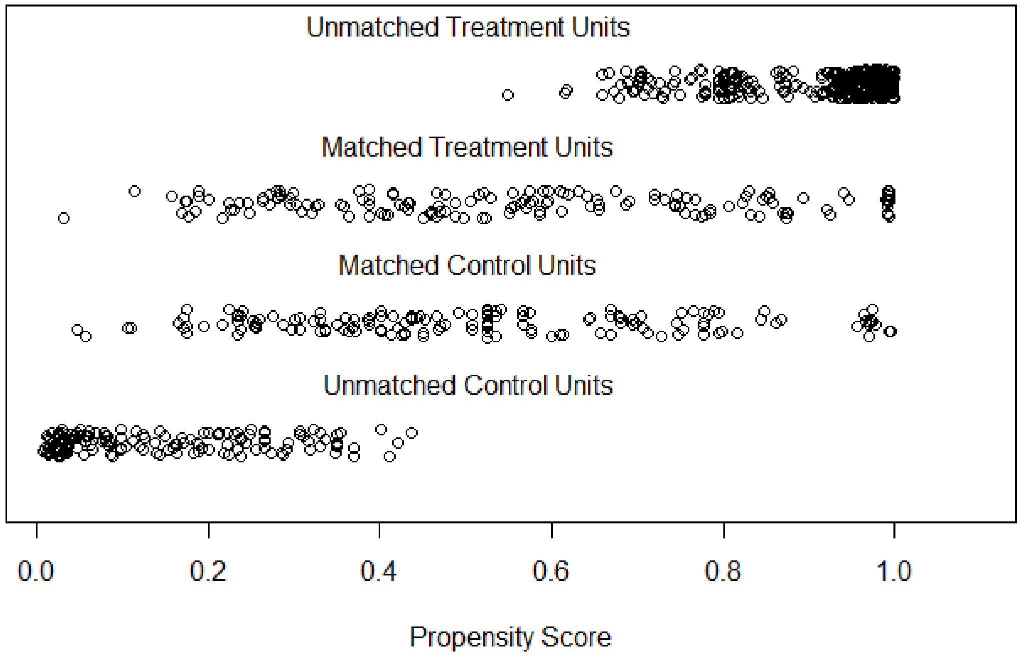

Figure A10. Graphic representation of propensity score matching results for control units being the natural land use: broad leaved forest and treatment units being the anthropogenic land use: pastures.

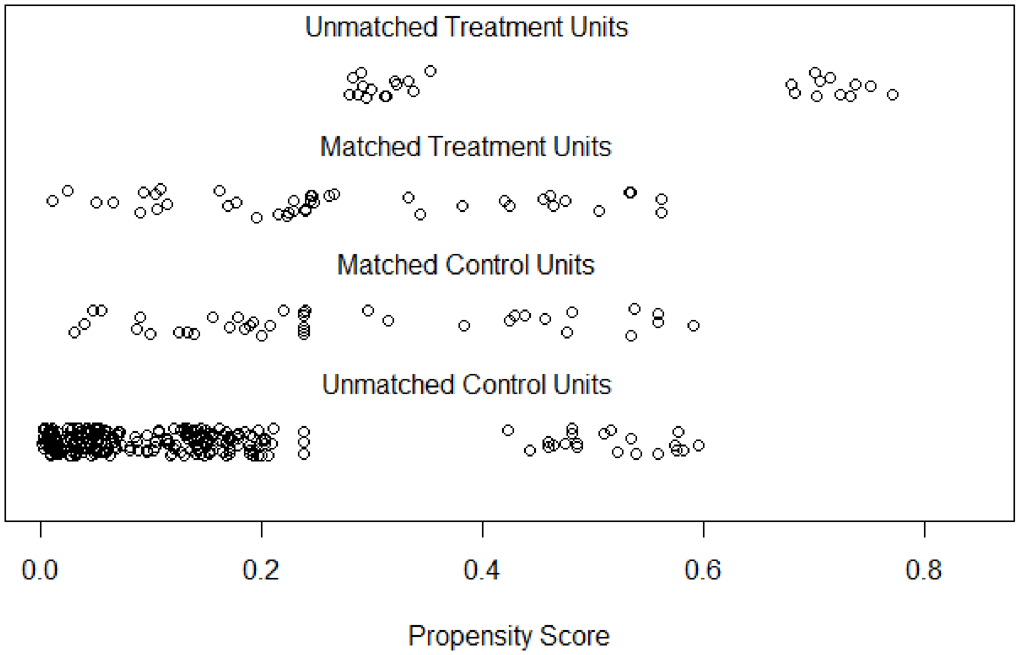

Figure A11. Graphic representation of propensity score matching results for control units being the natural land use: broad leaved forest and treatment units being the anthropogenic land use: complex cultivation patterns.

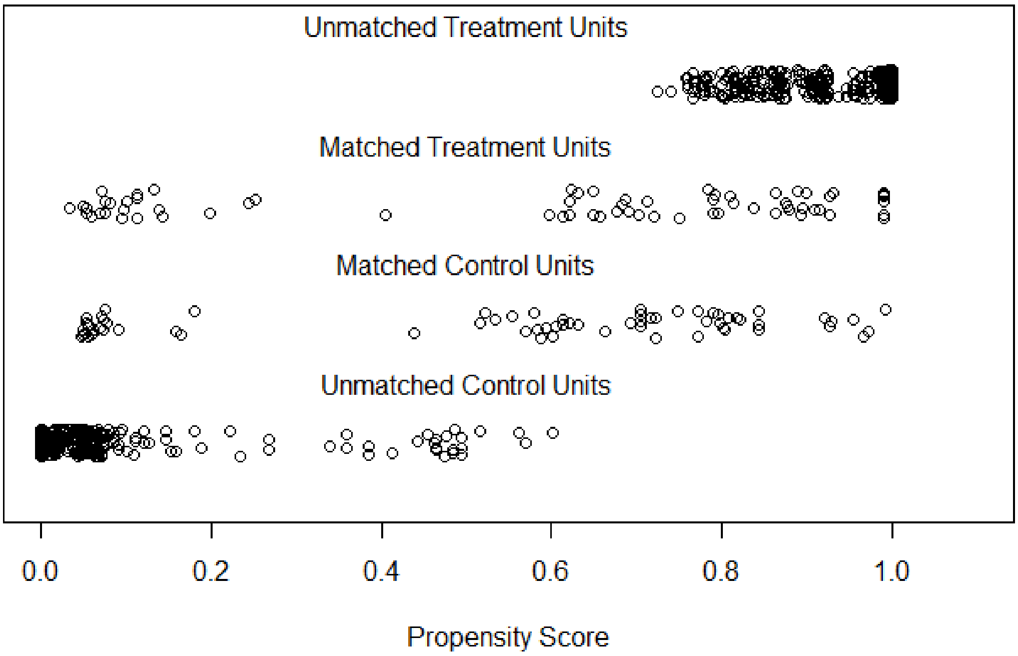

Figure A12. Graphic representation of propensity score matching results for control units being the natural land use: coniferous forest and treatment units being the anthropogenic land use: non-irrigated arable land.

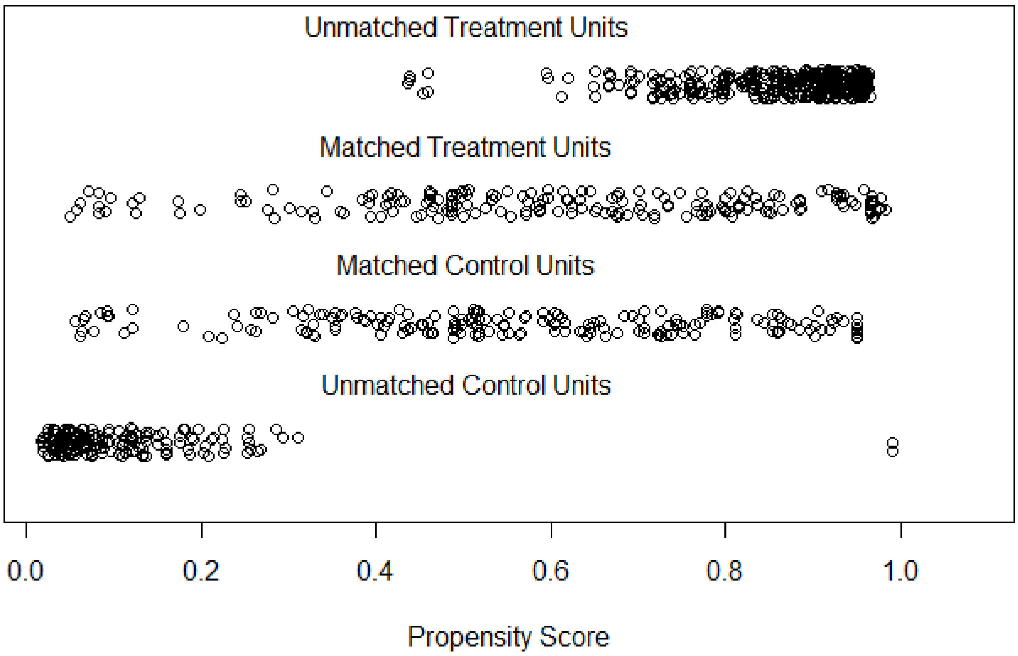

Figure A13. Graphic representation of propensity score matching results for control units being the natural land use: coniferous forest and treatment units being the anthropogenic land use: pastures.

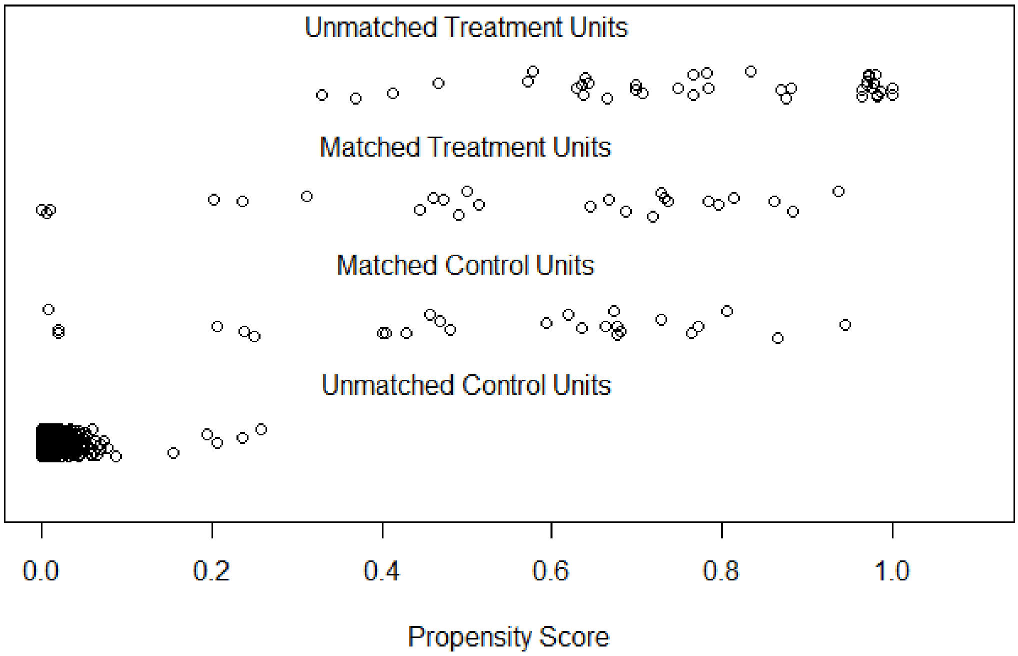

Figure A14. Graphic representation of propensity score matching results for control units being the natural land use: coniferous forest and treatment units being the anthropogenic land use: complex cultivation patterns.

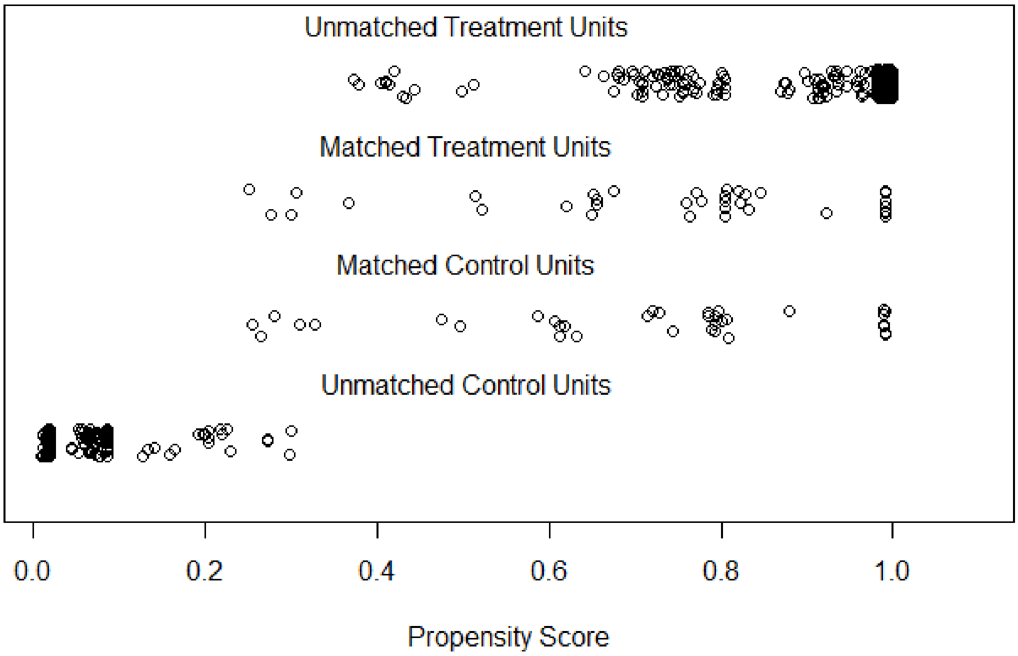

Figure A15. Graphic representation of propensity score matching results for control units being the natural land use: mixed forest and treatment units being the anthropogenic land use: non-irrigated arable land.

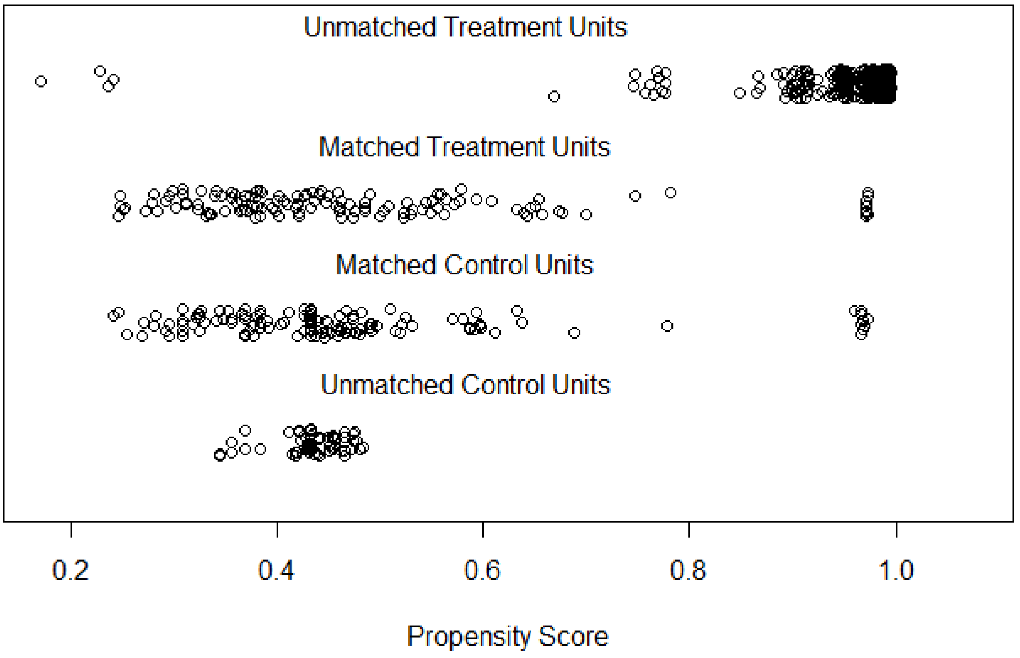

Figure A16. Graphic representation of propensity score matching results for control units being the natural land use: mixed forest and treatment units being the anthropogenic land use: pastures.

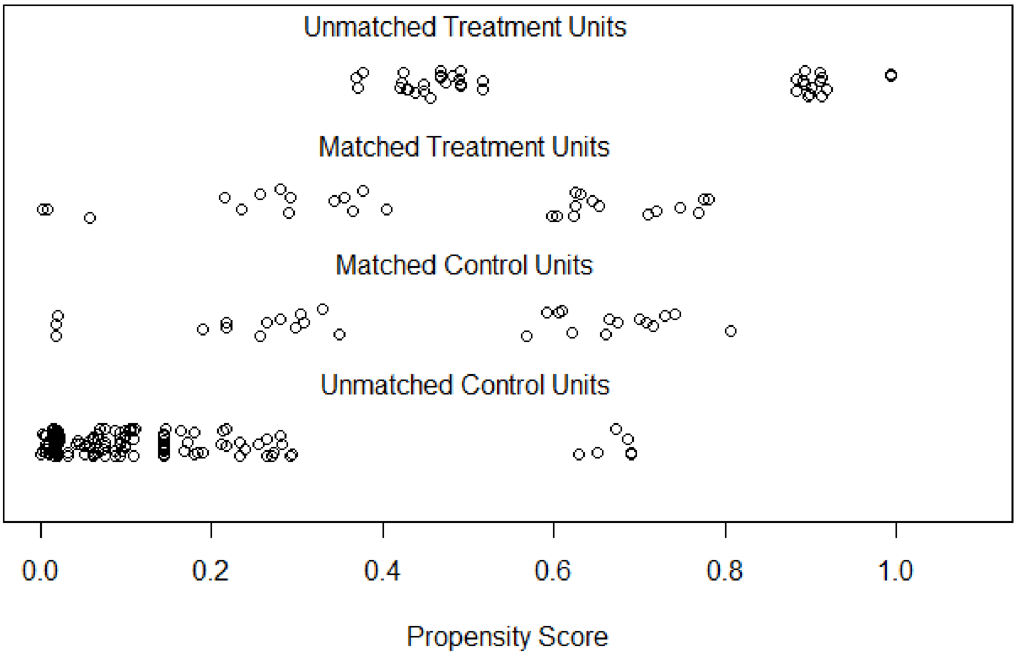

Figure A17. Graphic representation of propensity score matching results for control units being the natural land use: mixed forest and treatment units being the anthropogenic land use: complex cultivation pattern.