

SCALING UP SUSTAINABLE ROBUSTA COFFEE PRODUCTION IN VIETNAM: REDUCING CARBON FOOTPRINTS WHILE IMPROVING FARM PROFITABILITY

FULL TECHNICAL REPORT

By assignment of USAID Green Invest Asia, JDE and IDH

Agri-Logic M. Kuit, D.M. Jansen, N. Tjink

Date: 12 December 2020



Table of contents

Executive summary	4
1 Background	6
2 Introduction	7
2.1 Objectives	7
2.2 Research questions	8
2.3 Structure of the report	9
3 Methods	10
3.1 Data sources, harmonisation and data cleaning	10
3.2 Spatial and temporal coverage	10
3.3 Modelling of carbon footprint	15
3.4 Statistical analysis	17
4 Results	18
4.1 Carbon emissions	21
4.2 Carbon stocks and sequestration	34
4.3 Carbon footprint	39
4.4 Carbon footprint and farm profitability	50
4.5 Effectiveness of interventions	56
5 Conclusions	62
5.1 Carbon emissions	62
5.2 Carbon stocks	62
5.3 Carbon footprint	63
5.4 Carbon footprint and profitability	63
5.5 Effectiveness of interventions	63
6 Recommendations	64
6.1 Data	64
6.2 Interventions	66
6.3 Considerations for further research	67
7 References	68
Annex 1: Above Ground Biomass models	69
Annex 2: Summary table of main findings	72

Abbreviations

AGB	Above Ground Biomass
CO ₂ e	CO ₂ equivalent
DBH	Diameter at Breast Height
GBE	Green bean equivalent
GCP	Global Coffee Platform
GHG	Greenhouse Gas
Ha	Hectare
HDF	Highly Diversified Farm
ICO	International Coffee Organisation
K	Potassium
kWh	Kilo Watt Hour
MCF	Monocrop Farm
MDF	Medium-diversified Farm
Mt	Metric ton (1,000 kilogram)
N	Nitrogen
P	Phosphorus
SCM	Supply Chain Management
USD	US Dollar
VND	Vietnam Dong

DISCLAIMER:

This document is produced by PACT Thailand under the USAID Green Invest Asia project and made possible through support from the United States Agency for International Development (USAID). This document does not necessarily reflect the views of USAID or the United States Government.

Executive summary

In this report we analyze the carbon footprint of Vietnam's coffee production with a focus on the four key producing provinces in the Central Highlands: Dak Lak, Dak Nong, Gia Lai and Lam Dong. The study is carried out under contract to USAID Green Invest Asia, a technical services facility that supports sustainable agriculture and forestry business initiatives in Southeast Asia. In collaboration with Jacobs Douwe Egberts (JDE) coffee, IDH, and four of JDE's suppliers, the facility aims to stimulate investment in climate-friendly production. Coffee production with a reduced carbon footprint is one such climate-friendly production process.

The analysis is based on five years of data (2015-2020) from four suppliers (ACOM Vietnam, Louis Dreyfus Company, Mascopex, and Simexco) that collectively handle more than half the country's annual coffee output. Data for the analysis comes from the suppliers' data systems with a further contribution from the Global Coffee Platform; collectively we used records of 14,964 farmers.

Carbon emissions

Carbon dioxide equivalent (CO₂e) emissions were 3.21 Mt CO₂e/Mt green bean equivalent (GBE) in 2015/16 and have decreased significantly to 1.22 Mt CO₂e/Mt GBE in 2019/20. Fertilizer contributes more than 83 percent to emissions, with nitrogen being the single largest contributor. In the driest season, the contribution of energy use for irrigation is significantly higher than in seasons with more favorable rainfall.

CO₂e emissions per unit coffee vary significantly across groups of farmers with different yield levels. Farmers with yields of less than 1,250 kg GBE/ha have a 5-year average emission of 2.50 Mt CO₂e /Mt GBE versus 1.01 Mt CO₂e/Mt GBE among farmers with yields in excess of 3,500 kg/ha. This is driven largely by over-application of nitrogen by less productive farmers. Monocrop farmers (those with less than 15 percent non-coffee trees) emit significantly higher volumes of emissions per unit coffee than medium (15 percent- 30 percent non-coffee trees) and highly diversified (>30 percent non-coffee trees) farmers and in the two most recent seasons, also on a total emissions per ha basis.

Coffee yields over time are much more volatile on monocrop farms, yet their long-run average yield is significantly higher than that of medium-diversified farms, which in turn are higher than those on highly diversified farms. Emissions have gone down significantly from 2016/17 to 2018/19 and 2019/20, irrespective of the level of diversification. We think this is driven by a combination of project interventions and declining coffee prices over the same time frame resulting in lower fertilizer applications. In the absence of a control group or long-term project service delivery data, we cannot ascertain how much projects and coffee prices have each contributed to this change.

The three provinces for which we have data on emissions over time show diverging patterns. Emissions in Dak Lak have reduced significantly from 2016/17 to 2018/19 from 1.74 to 0.86 Mt CO₂e/Mt GBE. In Lam Dong, emissions show a similar trend, moving from 1.26 to 0.92 Mt CO₂e/Mt GBE in the same time frame. However, Gia Lai sees a significant increase, from 1.59 to 1.85 CO₂e/Mt GBE. At the district level, increases in emissions are predominantly found in Lam Dong province.

Carbon stocks and sequestration

Monocrop farms, which tend to be older, had carbon stocks of 41.6 Mt CO₂e/ha in 2016/17, significantly more than highly diversified farms whose tree stocks are larger but more recently planted. As coffee is replaced, the sample stabilizes and tree stocks on more diversified farms mature, the carbon stocks on medium and highly diversified farms (>42 Mt CO₂e/ha) outstrip that of monocrop farms (34.0 Mt CO₂e/ha) in 2019/20 by a significant margin.

Carbon footprint

The carbon footprint on a per hectare (ha) basis on highly diversified farms is significantly lower than on monocrop farms. In part this is because of higher carbon sequestration rates, but, more importantly, by lower emissions. Across the three levels of diversification, we observe a downward trend over time in carbon footprints per ha.

Nearly one-third of the highly diversified farms had a negative carbon footprint in the 2019/20 season. This is significantly higher when compared to monocrop and medium-diversified farms. Irrespective of the level of diversification, negative footprint farms spend significantly less on fertilizer, but their yields are also lower.

Across partners' various projects, we estimate that the 14,100 farmers they engage emit close to 74,000 Mt CO₂e per annum. At sector level in the Central Highlands, we estimate total net emissions to be just over 800,000 Mt CO₂e per year. Reducing these emissions can be achieved by increasing diversification, but a more impactful approach would be to particularly optimize nitrogen use. Moving 10 percent of the farmers closer to an assumed optimum of 120 kg N/Mt GBE would reduce net emissions by 6 percent. Instead, increasing the share of highly diversified farms by 10 percent would lower net emissions by 4 percent and runs the risk of increasing pressure on existing forest resources to make up possible supply shortfalls that are likely to result.

Carbon footprint and farm profitability

Farms with positive footprints are significantly more profitable than those with negative footprints, but those with footprints in excess of 1.0 Mt CO₂e/ha are not more profitable than those in the range from 0 to 1.0 Mt CO₂e/ha, indicating that net emissions in excess of 1.0 Mt CO₂e are not a prerequisite for profitable production.

Effectiveness of interventions

Partners' data on service delivery to farmers is only available for a small part of the population during the past two seasons. As such we are very limited in what we can analyze on how interventions are affecting farmers' performance and behavior. We see significantly lower nitrogen use among farmers in Dak Nong province who received soil tests, but the data covers only one season so we cannot control for pre-test nutrient management on those same farms. Overall, if partners want to know how interventions are affecting farmers' behavior, then complete service delivery data should be collected.

Recommendations

Programs that seek to lower the carbon footprint of coffee can, in our assessment, best focus on optimizing fertilizer use. Increasing diversification is also possible, but this intervention requires more long-term investment. From available data, it is not clear if farmers outside certain districts in Dak Lak and Dak Nong are keen to diversify. The short-term effect in footprint reduction is less than what can be achieved if farmers move closer to optimal fertilizer use, which has the added benefit of reducing their production costs.

While we analyzed many datasets, some topics remain unclear. A severe limitation was the discontinuity of much of the available data. We strongly recommend ensuring regular (i.e. seasonal) surveys of the same farmers to build a balanced panel data set, at least among partners' projects.

This study and a summary version are available for download at greeninvestasia.com/research.

I. Background

Vietnam is the world's second largest producer of coffee and the leading exporter of Robusta coffee (ICO, 2020). Production in the 2019/20 crop year was 31.3 million bags Green Bean Equivalent (GBE) and is expected to be 30.2 million bags in 2020/21. Exports in 2019 were 27.2 million bags, generating approximately 2.785 billion USD in revenue (ASEM Connect, 2019) and contributing around 10 percent to national agricultural export earnings (ICO, 2019). Robusta production is concentrated on around 565,000 hectares (ha) in the Central Highland provinces of Dak Lak, Lam Dong, Gia Lai and Dak Nong. In these provinces, approximately half a million small-scale farmers produce coffee on farms averaging just over 1 ha in size (SCC, no date).

USAID Green Invest Asia connects investors to agricultural and forestry companies that are raising capital for sustainable, low-emission projects. The program de-risks lending through improving clients' environmental performance and impact measurement (USAID Green Invest Asia, 2020). For this study USAID Green Invest Asia partnered with Jacobs Douwe Egberts (JDE) – one of the world's largest coffee and tea companies and a significant buyer of Vietnam coffee – IDH the Sustainable Trade Initiative, and four of JDE's suppliers to provide technical support to their sustainable coffee initiative in Vietnam's Central Highlands. JDE's Supply Chain Management (SCM) company partners – ACOM Vietnam, Louis Dreyfus Company, Simexco, and Mascoopex – are collectively responsible for trading more than half of Vietnam's annual Robusta coffee output. The partnership aims to enhance productivity of Vietnam's coffee sector, while reducing the environmental footprint of coffee production, especially greenhouse (GHG) emissions.

2. Introduction

Since 2016, JDE, IDH, and the SCM partners have made significant investments into sustainable coffee production and supply chains in Vietnam through collaborative programs with smallholder farmer producers. These programs are currently working with over 14,000 farmer households growing coffee on nearly 25,000 ha across four provinces in the Central Highlands to increase efficient use of inputs (particularly fertilizer and water), reduce GHG emissions, and improve overall farm profitability. Current project interventions include: promoting intercropping and farm diversification with fruit and shade trees; improving soil and nutrient (fertilizer) management; enhancing water and pesticide utilization, and other activities.

Previous analyses used production and farm data from a sample of 300 coffee farmers in Lam Dong and Dak Lak provinces. These analyses indicated the possibility of reducing the carbon footprint of coffee production while maintaining yields and improving overall farm profitability. One way is through a more efficient use of inputs such as fertilizers. Another way is increased carbon sequestration through planting more shade and fruit trees in typically monoculture coffee farms (IDH, 2019).

These findings demonstrate that the diversification of monocrop coffee farms along with optimizing fertilizer use are potentially viable strategies to transform Vietnam's Robusta coffee sector from being a carbon source to a carbon sink. However, as these findings are based on a limited population size, it can be inaccurate to extrapolate them across the broader landscape to inform a sector-level assessment of carbon emissions and sequestration connected to partner interventions. Fortunately, a greater quantity of data is now available covering the past several seasons from multiple partners working across several provinces with more farmers. Hence, the goals of this expanded study were to fill some of the data gaps, to better understand land use trends, and to inform strategies for scaling up effective approaches in Vietnam's coffee sector.

2.1 Objectives

The overall objectives of this study were to:

1. Analyze trends in coffee carbon footprints and farm profitability, utilizing more data sources;
2. Better understand the impact and effectiveness of current partner interventions in relation to efficient utilization of farm inputs (fertilizer, energy, water, labor, tree seedlings, etc.), carbon footprint (GHG emissions and carbon sequestration), and farm profitability, and;
3. Recommend effective approaches and interventions to increase carbon mitigation, and facilitate scale-up across Vietnam's coffee sector.

2.2 Research questions

To achieve these objectives, the focus was on a range of research questions across five categories:

1. Carbon emissions

- 1.1 What are the carbon equivalent emissions in metric tons of CO₂ equivalent (CO₂e) per metric ton coffee (Mt CO₂e/Mt GBE) by source (fertilizer and energy) and season for the four target seasons? Are there correlations with weather/climate patterns, for example, increased water and energy use in drier years?
- 1.2 What are the CO₂e emissions by source and yield, level of diversification (monocrop, medium-diversified, highly diversified), and for the four target seasons?
- 1.3 What are the changes in CO₂e emissions and yields during the four harvest seasons by agroforestry type?
- 1.4 What are the differences in carbon emissions over time between the target geographies (provinces and districts, and communes, where possible)?

2. Carbon stocks and sequestration

- 2.1 How have carbon stocks per hectare by agroforestry type and season changed over the four harvest seasons?
- 2.2 How have carbon stocks per hectare by agroforestry type and season changed over the four harvest seasons between the target geographies (provinces and districts, and communes, where possible)?

3. Carbon footprint

- 3.1 What are the CO₂e emissions and sequestration by farm and agroforestry class for each season?
- 3.2 What is the share of farmers and emission-sequestration balance by agroforestry class? How has this changed over time and in each of the target provinces?
- 3.3 What are the carbon emissions, sequestration, and footprint by agroforestry class for each year, and disaggregated for each of the target geographies (provinces and districts, and communes where possible)?
- 3.4 How do these carbon footprint estimates compare with national, international, and other relevant benchmarks for Robusta coffee?
- 3.5 Based on these estimates, what is the overall amount of CO₂e emissions for the entire population of farmers engaged in the program? What emissions reduction scenarios can be achievable across the entire Central Highlands landscape?

4. Carbon footprint and farm profitability

- 4.1 What is the relationship between carbon footprint and farm profitability? Are lower carbon footprint farms generally more profitable (in Vietnamese Dong/ha/season) than higher carbon footprint farms? What farm management practices are responsible for this desired outcome (i.e. are there significant differences between farms using organic inputs only versus those using inorganic inputs such as NPK fertilizer)?
- 4.2 To what degree may higher carbon footprint farms be more profitable, or lower carbon footprint farms less profitable? What specific farm management practices are responsible for these outcomes?
- 4.3 What are the differences in these trends across the four harvest seasons in target geographies (provinces and districts, and communes where possible), and for different ethnic groups (where possible)?

5. Effectiveness of interventions

- 5.1 How have trends in fertilizer use changed over the four harvest seasons in the target geographies (provinces and districts, and communes where possible)?
- 5.2 How have trends in farm diversification and intercropping changed over the four harvest seasons and in the target geographies (provinces and districts, and communes, where possible)?
- 5.3 Which interventions and activities implemented by SCM partners are the most effective/have the greatest impact reducing carbon footprints?
- 5.4 What is the uptake rate of these interventions by targeted farmers? How long, in general, does it take for interventions to demonstrate an impact on emissions?

From this, recommendations will follow on what SCM partners can do to enhance the effectiveness and scale of their impacts in the Central Highlands Robusta coffee landscape.

2.3 Structure of the report

Section 3 of this report will outline the study methodology with details on the data used, how it was cleaned/analyzed, and descriptions of the models developed to estimate the carbon footprint. We discuss results in Section 4. Each category of research questions is discussed under a separate sub-section. At the start of each sub-section, we summarize the conclusion from that sub-section. Conclusions and recommendations are outlined in Sections 5 and 6, respectively.

3. Methods

3.1 Data sources, harmonization and data cleaning

Four SCM partners provided data for 14,964 farmers across four provinces covering 2015/16 to 2019/2020; the majority are from in-company data systems. A sub-set of 750 farmers who maintained Farmer Field Book records¹ were also included. In addition, the Global Coffee Platform (GCP) supplied data of 1,000 farmers in two districts. GCP data partly overlapped with data provided by two of the SCMs. One of the SCMs relies on the GCP data collection tool to obtain its farm level data, so its data set was similar to GCP. The remaining partners each have their own proprietary data collection system; while there is some data overlap, there are differences, too. To enable sound analysis, we inventoried the variables in each dataset and compared them to what we required to answer the research questions. We then created a consolidated dataset that maximized the number of observations on the required study variables.

The next step was to harmonize data for key variables such as province, district, and commune. The same location was found to be spelled or abbreviated in numerous ways by different partners and even within datasets of the same partner. Names of tree species were also harmonized. Because there are 15 different ways to write what is essentially the same material, rather than harmonizing them, we built a more flexible algorithm for fertilizer-related calculations.

Not all farmers have data on the required variables. In some cases, we could impute missing data by using known correlations with other variables. For example, irrigation water volume is known to correlate with energy use, often most strongly at commune level. Where the amount of energy used is missing, we can impute it from irrigation volume. Several data sets only indicated that farmers used NPK fertilizer, but not the exact type. As emissions are driven predominantly by fertilizer use and nitrogen fertilizer makes up the majority of fertilizer-related emissions, knowing the type of NPK is crucial. Where NPK types are missing, we assume farmers used NPK 16-8-16, the most commonly used NPK type. In around of half of all fertilizing activities, our data showed farmers use a form of NPK and if NPK is used, 31 percent of the times this is NPK 16-8-16.

Specific calculations ignore outliers on certain variables where values are clearly outside the bounds of what is possible, and their inclusion would disproportionately affect calculations. In this way, data from a farmer with outliers on one or two variables can still be used in other calculations where the variables with outliers do not play a role. For example, yield values are ignored if they exceed 7,000 kg GBE/ha. Fertilizer application values converted to single element values are ignored if they exceed 2,500 kg/ha of nitrogen (N), 1,000 kg/ha of phosphorus (P), or 3,000 kg/ha of potassium (K). Farms with variable production costs in excess of 100 million VND/ha (4,343 USD) are excluded. Farms where the sum of all trees (coffee and other species) exceeds 2,500 trees/ha are also excluded.

3.2 Spatial and temporal coverage

Across the four provinces, we estimate Robusta coffee is grown in 400 communes across 42 districts (VCC&C, 2019). Our dataset covers four provinces, 22 districts with Robusta coffee and two districts with Arabica, and 114 communes. Only 80 out of 114 communes could be matched to geospatial files. We therefore analyze geographical data at the district level where no mismatches occurred. Our sample includes all of the higher production districts in Lam Dong, Gia Lai, and Dak Lak. In Dak Nong, coverage is more limited (*Figure 1*).

¹ All SMC partners, except Mascopex, participated in a project activity around the Farmer Field Book for varying durations of time. The FFB is an Agri-Logic-developed system where farmers keep daily records of their farm management. These are collected and digitised bi-weekly and analyzed seasonally.

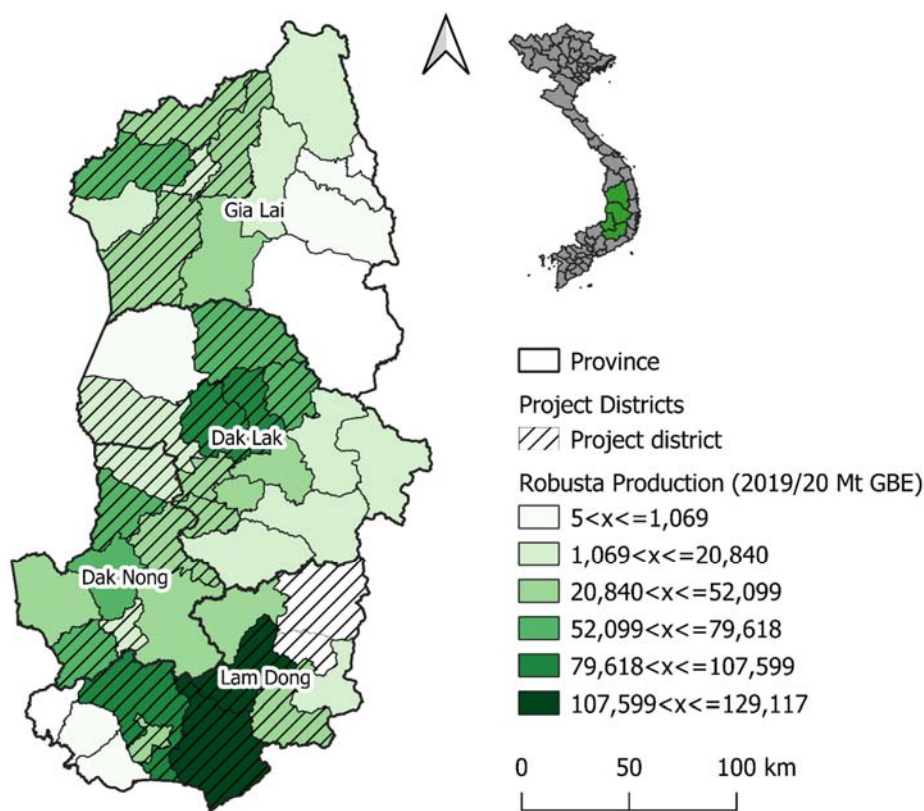


Figure 1: Spatial coverage of sample by province and district. Shaded areas indicate districts for which observations are available in the sample. Shades of green indicate estimated production levels for the 2019/20 season. Source: author's graph with crop data (VCC&C, 2020) and GIS base map (UNHDE, 2019). Note that Lac Duong and Da Lat in North-East Lam Dong are Arabica areas and hence do not show Robusta production values.

Figure 1 shows a small number of mid-level production districts not being covered, such as Chu Se in Gia Lai province and Tuy Duc, Dak Glong, and Dak Song in Dak Nong province. In all provinces, at least half of the coffee-producing districts with meaningful production (over 1,100 Mt GBE) are included in the sample. Companies tend to concentrate their project activities in certain districts. In Dak Lak this means that two districts, Buon Don and Krong Nang, are over-represented and in Lam Dong, farmers in the sample are predominantly located in one district, Di Linh. In Gia Lai, the distribution of farmers across districts is more even, although coverage in Chu Prong is not ideal (Table 1).

Table 1: Total area with coffee by districts in the sample and by province as well as total coffee area in the sample. The number of districts not in the sample is listed in brackets.

Province	District	a. Area (ha)	b. Area in sample	Share (b/a*100%)
Dak Lak	Buon Don	2,936	487	17%
	Buon Ho	14,391	166	1%
	Buon Ma Thuot	13,194	487	4%
	Cu M'gar	37,690	481	1%
	Ea H'leo	26,270	80	0%
	Krong Ana	8,827	452	5%
	Krong Nang	25,305	5,252	21%
	Not in sample (7)	66,719		
Total Dak Lak		195,333	7,404	4%
Dak Nong	Cu Jut	3,386	125	4%
	Dak Mil	24,831	288	1%
	Dak R'lap	22,844	831	4%
	Gia Nghia	5,662	186	3%
	Krong No	11,342	95	1%
	Not in sample (3)	53,237		
Total Dak Nong		121,302	1,525	1%
Gia Lai	Chu Pah	8,041	1,320	16%
	Chu Prong	15,021	202	1%
	Dak Doa	13,227	762	6%
	Ia Grai	20,955	3,850	18%
	Pleiku	4,512	888	20%
	Not in sample (8)	21,466		
Total Gia Lai		83,221	7,022	8%
Lam Dong	Bao Lam	39,091	399	1%
	Bao Loc	8,879	74	1%
	Di Linh	47,821	5,987	13%
	Da Lat	n.a.	n.a.	n.a.
	Duc Trong	11,264	10	0%
	Lac Duong	n.a.	n.a.	n.a.
	Lam Ha	42,407	116	0%
	Not in sample (5)	15,784		
Total Lam Dong		165,246	6,586	4%
Grand total		565,102	22,527	4%

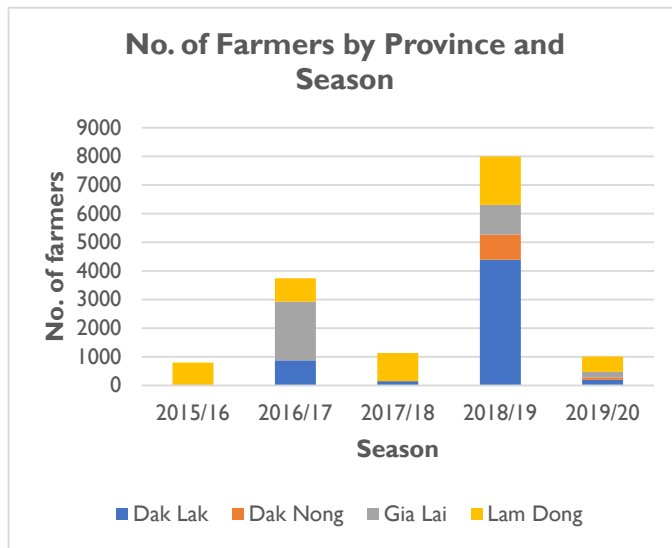


Figure 2: Number of observations in sample by province and season

other seasons are more poorly covered (Figure 2).

Also, we need to consider the variance of required key variables. This, in combination with a desired margin of error and confidence interval, indicates whether the sample is representative. We used the average and the standard deviation of each of these variables in each province and each season and set the desired confidence interval and error margin to 90 percent and 5 percent respectively. We calculated the minimum required sample size for each province in each season:

$$\text{sample size} = \frac{z \text{ score}^2 * \text{standard deviation}^2}{\text{margin of error}^2}$$

Given that the standard deviation of a variable is used in this calculation, different variables likely require varied sample sizes in different provinces and seasons. We then compare outcomes with available observations in the dataset (Table 2).

At district level, coverage of the sample is incomplete. Nevertheless, in three provinces we include farmers in half or more of the coffee-producing districts in the sample. In Gia Lai, the only province where coverage is below 50 percent, we reach 42 percent.

Besides geographic coverage, we also consider whether temporal coverage is sufficiently representative. This is necessary for accurately answering the research questions that include change over time of input use, emissions, and carbon footprint. We find that temporal distribution is highly skewed, with the bulk of observations covering the 2018/19 season. The 2016/17 has close to 4,000 observations, but the

Table 2: Required sample size by province and season to report representatively on fertilizer, tree stocks, yield, and training. Green cells indicate the available sample exceeds the required minimum sample. Red cells indicate the reverse. Orange cells are within -10% of the required sample and may just be useable. Grey cells indicate no observations available. The values indicate the required sample size.

	Season				
	2015/16	2016/17	2017/18	2018/19	2019/20
COFFEE TREES					
Dak Lak		4	10	69	50
Dak Nong				39	86
Gia Lai		0			32
Lam Dong	0	5	1	144	2
NON-COFFEE TREES					
Dak Lak		333	304	207	303
Dak Nong				155	
Gia Lai				240	
Lam Dong		2210	1912	207	2731
FERTILIZER COST					
Dak Lak		322	241	314	307
Dak Nong				109	211
Gia Lai		447		364	401
Lam Dong	301	447	362	527	345
IRRIGATION WATER					
Dak Lak		365	191		159
Dak Nong				604	
Gia Lai		415		8727	
Lam Dong	573	754	483	2865	337
YIELD					
Dak Lak		45	148	132	148
Dak Nong				224	142
Gia Lai		23			147
Lam Dong	122	221	192	272	240
ACCESS TO SERVICES					
Dak Lak				226	54
Dak Nong				173	76
Gia Lai		87		109	34
Lam Dong				23	

3.3 Modelling of carbon footprint

Carbon sequestration or carbon dioxide (CO₂) removal is the long-term removal, capture or sequestration of carbon dioxide from the atmosphere to slow or reverse atmospheric CO₂ pollution and to mitigate or reverse global warming. Trees play an important role in carbon sequestration, by keeping the CO₂ in the wood, where it stays until trees die and decompose, or are cut and burned.

To estimate the carbon stocks and rate of sequestration we build on the following:

1. First, we should know which species of trees are in the farms, and the trees' age, as generally older trees sequester more CO₂. The farmers in the projects inform us the year of planting. We use the Plant Year (or start year) and the Current Year. The difference between the Plant Year and the Current Year indicates how many years the trees have grown.
2. Second, we have to know how fast the trees grow and how that can be calculated. This is normally done with general allometric equations, such as $Y = a \cdot (X^b)$ or $Y = a \cdot X + b$. For us, Y is a biological variable (such as tree height or Diameter at Breast Height = DBH), a is a proportionality coefficient, b is the scaling exponent (which is equal to the slope of the line when plotted on logarithmic coordinates), and X is some physical measure such as Age. From this we can estimate the total volume of the tree and by multiplying that with the wood density, we estimate the Above Ground Biomass of trees on a farm based on their age.
3. Lastly, we need to know the carbon content of species-specific biomass, with which we convert the biomass estimation into a CO₂e value. This value typically lies between 0.45 and 0.55; we use a standard value of 0.47 (IPCC, 2006). This then gives us C values which are multiplied by 3.67 to arrive at the CO₂e stock values. Changes in stocks from one year to the next is effectively the rate of sequestration on a specific farm. Note that in our model this is not just driven by building up stocks, but also by trees that may have been removed from the farm.

Several of the allometric equations to estimate Above Ground Biomass in relation to the age of trees comes from previous unpublished work by Agri-Logic. Others were derived from literature ([Table 3](#) and Annex I). We then use the farm level tree stock information (species, numbers and years in which trees were planted) to build up farm level stock estimations of Above Ground Biomass and C stock values. The difference in stock on the same farm from one season to the next is the rate of sequestration. This can be negative on a farm if the CO₂e volume contained in trees that were removed outstrips the stock increase among those that were left standing.

Table 3: Allometric equations by species and source, where AGB=Above Ground Biomass (kg/tree); Age=Year(s) After Start Growth

Species	Common name	Allometric equation	Source
<i>Acacia oraria</i>	Acacia	$AGB = 0.703*(Age^2) + 16.783*Age$	Agri-Logic
<i>Hevea brasiliensis</i>	Rubber	$AGB=0.0939*(Age^{3.0928})$	Agri-Logic
<i>Cassia spec.</i>	Cassia	$AGB=12.782*(Age^{1.3226})$	Agri-Logic
<i>Oroxylum indicum</i>	Midnight horror	$AGB=2.3881*(Age^{1.4818})$	Agri-Logic
<i>Artocarpus heterophyllus</i>	Jackfruit	$AGB=11.669*(Age^{1.1854})$	Agri-Logic
<i>Durio zibethinus</i>	Durian	$AGB=3.2868*(Age^{1.5433})$	Agri-Logic
<i>Ceiba pentandra</i>	Kapok	$AGB=3.528*(Age^{1.308})$	Agri-Logic
<i>Coffea canephora</i>	Robusta coffee	$AGB=18.17*(Age^{0.4602})$	Agri-Logic
<i>Persea americana</i>	Avocado	$AGB=2.7856*(Age^{1.5048})$	Agri-Logic
<i>Kibatalia laurifolia</i>	Lồng mức (no English common name)	$AGB=2.9883*(Age^{1.352})$	Agri-Logic
<i>Anacardium occidentale</i>	Cashew	$AGB = 43.807*(Age^{0.6132})$	Agri-Logic, based on Malimbwi (ed.), 2016
<i>Litsea glutinosa</i>	Litsea	$AGB=3.1879*Age-1.333$	Agri-Logic, based on Huy, 2009
<i>Piper nigrum</i>	Pepper	$AGB=0.11*0.33*(((0.7114*Age)+1.8409)^{2.2062})$	Agri-Logic

Farmers often use equipment that requires energy (like diesel, petrol, electricity) and materials which have embedded carbon emissions (like fertilizers). With diesel, petrol, and electricity we need to see how much fuel or electricity a farmer uses. For diesel and petrol, fixed emission factors are available from the Intergovernmental Panel on Climate Change (IPCC, 2006); 2.64 kg CO₂e/l of diesel and 2.392 kg CO₂e/l of petrol. For electricity, emission factors are per country, depending on their mix of power generation means (Brander et al, 2011). For Vietnam, a factor of 0.5164 kg CO₂e/kWh is used.

In Vietnam, there are a vast number of fertilizers available in the market. In the partners' dataset, we identified 448 unique fertilizers, all with different names and nutrient contents. To calculate the fertilizers' emissions, we take the following approach:

1. For each farmer, inventory how much of which fertilizer types have been used.
2. Now we have to know how much effective volume is available. With the fertilizer "16-8-16", we calculate the following: For nitrogen: $1000 \text{ kg} * 0.16 = 160 \text{ kg}$; P_2O_5 : $1000 \text{ kg} * 0.08 = 80 \text{ kg}$; and K_2O : $1000 \text{ kg} * 0.16 = 160$. Left over of the 1000 kg is $1000 - (160+80+160) = 600 \text{ kg}$. We assume that this remnant is not useable.
3. The next step is to find the kg CO_2e factor per kg N (or P_2O_5 or K_2O) when fertilizers are being produced and used. However, there are many different types of fertilizers, with different ways of being produced and used. Many of the fertilizers in the data set do not have a clear description of the type of nitrogen and other nutrients in the fertilizers. Where the type is unclear, we apply a value of 8.98 kg CO_2e /per kg N where we use Urea, as this is, by our estimation, the most commonly used source of nitrogen for coffee production in Vietnam. For P_2O_5 we use an emission factor of 0.37 based on 0-16.5-0 as standard and for K_2O we use 0.91 on basis of the standard Potassium chloride. Organic materials are factored in at 0.24 kg CO_2e per kg.

Emissions calculations require a linear discounting of emissions from land use conversion assigned to the current crop over the first 20 years after conversion. This requires information on previous land use not currently available. Most farms (75 percent) were established prior to the year 2000. These two combined factors permit us to ignore emissions from land use changes. Belowground carbon and soil carbon pools were also excluded from the analysis due to lack of currently available data.

The calculation modules for stocks and emissions are programmed in Visual Basic for Applications.

3.4 Statistical analysis

The data was analyzed in a combination of Microsoft Excel 365 and Stata SE13 -statistical software developed by StataCorp to identify statistically significant geographical and temporal variation in outcomes. We applied comparison of group tests for the different regions and over time with the following approaches:

Where we compared multiple groups, Levene's test for equal variance was applied among these groups. In case equal variance was not being rejected, we applied ANOVA analysis – with a TukeyHSD post-hoc test for comparing between group differences. When equal variance among groups was rejected, we applied Kruskal Wallis analysis, a non-parametric equivalent of ANOVA. In that case, between-group differences in those cases were tested by applying Dunn's test for stochastic dominance among groups. The false discovery rate was controlled using the Benjamini-Hochberg stepwise adjustment.

4. Results

The results are grouped by research question headers. Below each heading is a concluding sub-header that summarizes outcomes.

Based on data from 14,964 farmers in Dak Lak, Dak Nong, Gia Lai and Lam Dong provinces across five seasons, the average coffee farm size is 1.63 ha with an average 978 coffee trees per ha. Total tree stocks per ha of all species combined amount to 1,112 trees, so 13 percent of the tree stock are non-coffee species. Fertilizer application levels over this same time frame average just under 2 Mt/ha, while long-run average yields come in at 2.80 Mt GBE/ha. We have gender data for 3,725 farmers in the sample. Of this group, 20 percent is female.

Farm profiles differ somewhat between geographical locations ([Table 4](#)). Farm sizes are significantly different between all provinces, with the smallest farms found in Dak Lak and the largest in Gia Lai province. Yields in this sample differ too, only Lam Dong and Dak Lak are statistically similar ($p=0.05$). We tend to see somewhat higher yields of Robusta in Lam Dong, but we have a sub-group of Arabica farmers (11 percent of the sample) there who have somewhat lower yields. Diversification is significantly more prevalent in Dak Lak and Dak Nong.

Within these provinces, the central districts of Dak Lak and two districts in Dak Nong stand out with relatively high shares of highly diversified farms. In both Gia Lai and Lam Dong we find no districts where more than 11 percent of the farms fall in the highly diversified category and typically it is less than 3 percent ([Figure 3](#)).



Figure 3: 5-year average share of Highly Diversified Farms by District

Table 4: Farm size, 5-year average yields and share of non-coffee trees by province. Post-hoc comparisons of each using Tukey's HSD. Mean values shown. Letters indicates the mean difference is significant at the 0.05 level. Significance on gender variable not indicated as majority of gender data is

Province	Share females in sample	Farm size (ha)	Fertilizer use (Mt/ha)	Yield (Mt/ha)	Share of non-coffee trees
Dak Lak	12%	1.32 ^a	1.83 ^a	2.76	31% ^a
Dak Nong	No data	1.59 ^b	2.14 ^b	2.57 ^a	20% ^b
Gia Lai	28%	1.97 ^c	2.88 ^c	3.27 ^b	1%
Lam Dong	11%	1.74 ^d	1.46 ^d	2.68	<1%

missing.

The level of diversification definitions used in this study are based on work done by Agri-Logic in 2016 (IDH, 2017). We use the ratio of non-coffee trees on a farm to classify them according to their level of diversification. (Table 5).

Table 5: Share of farmers in sample by level of diversification and planting density of most commonly used tree species.

		Level of diversification		
		Monocrop	Medium-diversified	Highly diversified
	Share of sample	66%	7%	27%
Planting density (#/ha)	Coffee	1,008	996	882
	Non-coffee	10	309	940
	Pepper	2	151	519
	Cassia	2	107	339
	Avocado	2	19	34
	Durian	2	17	29
	Acacia	0	2	8
	Cashew	1	9	4
	Rubber	0	0	1
	Midnight horror	0	0	1
	Kapok	0	0	1
	Lồng mức (no English common name)	0	0	1
	Litsea	0	1	0

Table 5 shows the most commonly used cash-crop species to diversify are pepper, avocado and durian. Within the averages, variations in diversification are obscured. If we take ranges of planting densities for the most popular species, we can identify a number of different strategies within each category of diversification (Table 6).

Table 6: Share of farmers by range of planting density of main diversification cash crop within each level of diversification.

Species	Planting density (# trees per ha)		Level of diversification		
	From	To	Monocrop	Medium-diversified	Highly diversified
Pepper	0	0	96%	9%	1%
	0	100	3%	18%	1%
	100	300	0%	71%	26%
	>300		0%	2%	72%
Durian	0	0	85%	46%	37%
	0	20	12%	28%	20%
	20	80	3%	23%	36%
	>80		0%	3%	6%
Avocado	0	0	89%	46%	32%
	0	20	7%	23%	18%
	20	80	3%	27%	42%
	>80		0%	4%	8%

Table 6 shows that monocrop farmers are more likely to diversify with durian and avocado, with just 3 percent of them grow some pepper with planting densities of up to 100 vines/ha. This low level of pepper planting is somewhat more common on medium-diversified farms where close to one-fifth of farmers work with this number. Farmers mostly adhere to the recommendation several partners have made of planting no more than 80 durian or avocado trees per ha, Very few farmers in any of the categories of diversification plant in excess of that for these two species. Among the highly diversified farms it tends to be pepper that pushes them into this category, but those farms also show a greater likelihood to have higher planting densities of other non-coffee species.

4.1 Carbon emissions

In this section we review the emissions per Mt of GBE, and change in emissions over time. We do this both for the overall sample as well as by level of diversification and in relation to yield levels. We also explore geographical variations of emissions over time.

4.1.1 Carbon emissions by source and season

Carbon emissions were 3.21 Mt CO₂e/Mt GBE in 2015/16 and have gone down significantly to 1.22 Mt CO₂e/Mt GBE in 2019/20. Fertilizer contributes more than 83 percent to emissions, with nitrogen being the single largest contributor. In the driest season, the contribution of energy use for irrigation is significantly higher than in seasons with more favorable rainfall.

Some of the farms in the sample are intercropping coffee with other crops such as pepper, avocado or durian. On such farms we allocate emissions from fertilizer and energy directly proportional to the harvested volume of coffee as a share of the total harvested tonnage of all crops. On average, coffee makes up 92 percent of the total harvested tonnage. **Across the entire sample, emissions from fertilizer and energy per Mt of GBE have been on a downward trajectory.** In 2015/16 total emissions came in at 3.21 Mt CO₂e per Mt of GBE and have since dropped to 1.22 Mt CO₂e in 2019/20 (Figure 4).

If we isolate the two years for which we have an ample number of observations, i.e. the seasons 2016/17 and 2018/19, we observe a decline from 1.58 to 1.05 Mt CO₂e/Mt GBE. A subsequent ANOVA and Tukey's HSD test shows that the difference between the 2016/17 and 2018/19 season is significant ($p=0.05$), but so is the increase we observe from 2018/19 to 2019/20. Still, the emission level in 2019/20 is significantly lower than what it was during the first three seasons for which we have data available.

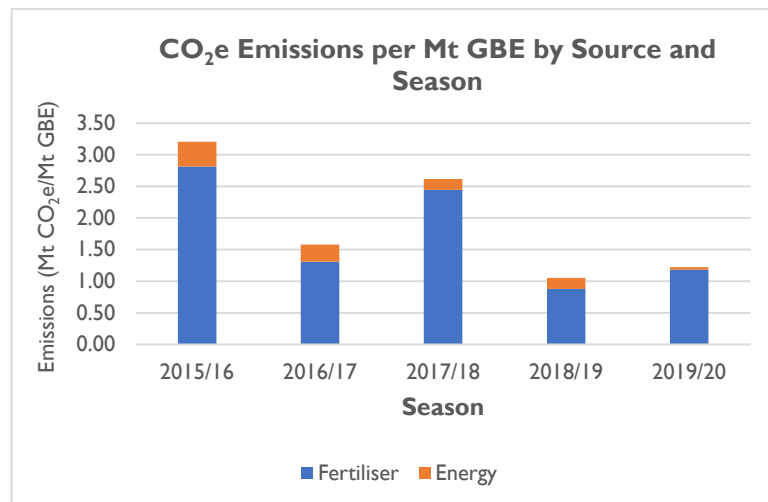


Figure 4: Emissions in Mt CO₂e/Mt GBE by season, split by fertilizer and energy emissions

The downward trend in emissions over time is caused by both significantly lower fertilizer and energy related emissions (Table 7). When we control for panel data imbalance, i.e. by plotting the emissions only for those farmers for whom we have data in both the 2016/17 and 2018/19 seasons, the numbers change, but the overall trend remains the same, so the inflow of new farmers into the sample and farmers dropping out of the sample are not driving the observed decline.

Table 7: Post-hoc comparisons of fertilizer and energy related emissions per Mt of GBE by season using Tukey's HSD. Mean difference shown. * indicates the mean difference is significant at the 0.05 level. "dd" indicates a very dry season, "d" indicates a dry season.

		Season (difference from base)				
		2015/16	2016/17	2017/18	2018/19	2019/20
Fertilizer emissions	Base season					
	2015/16	-	-1.50*	-0.37*	-1.93*	-1.63*
	2016/17		-	+1.13*	-0.43*	-0.13
	2017/18			-	-1.57*	-1.26*
	2018/19				-	+0.30*
	2019/20					-
Energy emissions	2015/16 ^{dd}	-	-0.12*	-0.25*	-0.22*	-0.35*
	2016/17		-	-0.13*	-0.09*	-0.23*
	2017/18			-	+0.03	-0.10*
	2018/19				-	-0.13*
	2019/20					

Emissions from fertilizer cover all recorded nutrient applications, irrespective of source. These emissions, therefore, also include emissions from applications of compost, manure, coffee husk and other organic materials. While Figure 4 shows that fertilizers are a strong driver for emissions at farm level, it is relevant to understand the relative contribution of N, P and K applications to those emissions. Farmers use a wide range of fertilizer types; we found 448 unique fertilizer names.

As nutrient contents vary between fertilizers and farmers may change the fertilizer types they use over time as result of economic constraints, training on Good Agricultural Practices or for other reasons, we checked the relative contribution of N, P and K-related emissions to total fertilizer emissions across the seasons (Figure 5).

The contribution of N declines over time. We have observed that excess application of N can be a problem in Vietnam's Robusta production (IDH, 2019). The relative decline of N-based

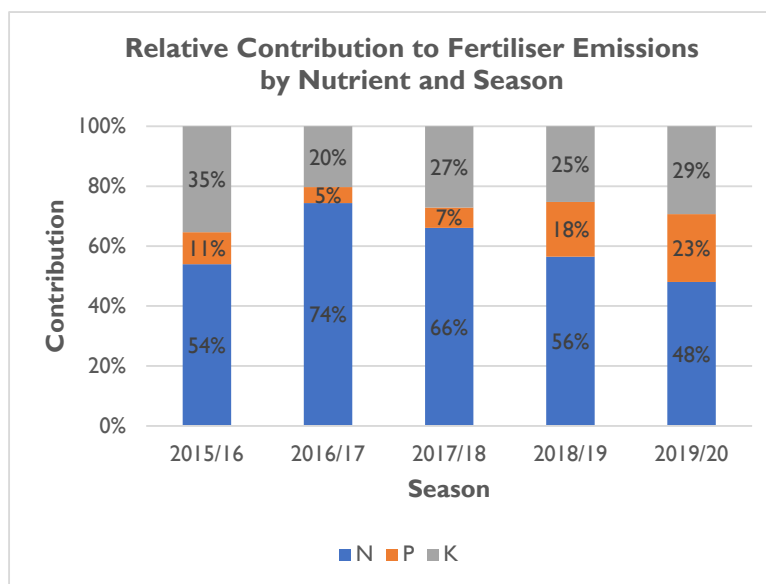


Figure 5: Relative contribution of N, P and K related emissions to total fertilizer emissions

emissions in combination with declining emissions from fertilizer is a welcome development. A planned analysis for 2020/21 season with a sufficiently large sample could indicate if the current trend continues.

Emissions from energy include emissions from the use of petrol, diesel, and electricity for various purposes, but predominantly for irrigation water pumping. In this data set, emissions from energy contribute between 3 percent and 17 percent of total emissions, depending on the season. This is notably lower than what we find in Farmer Field Book (FFB) data where it tends to contribute 27 percent (IDH, 2019). A study by CIAT (Nguyen-Duy et al, 2018) found values ranging from 11 percent to 19 percent in Dak Lak, depending on the cropping system. We think the data we have here, although on average close to the CIAT findings, is likely to be an under-estimation of energy's contribution to emissions. Most of the data we use here is collected with a once-a-year survey and the majority of farmers do not keep detailed records. While farmers are likely to remember their production of the previous season, the amount of fuel or kWh of electricity used for, say irrigation, is unlikely to be accurate.

One would expect greater energy use in drier seasons as farmers are more likely to apply more irrigation water under such conditions. We find significant differences over time ($p=0.05$) with reduced energy emissions in later seasons compared to the 2015/16 season (which was exceptionally dry), but also for all but one of the inter-season comparisons ([Table 7](#)).

The trend we observe indicates that energy use per Mt GBE has reduced over time. The relation between a season being abnormally dry and energy use is present, but is not as clear cut as one might expect. The 2015/16 season was the driest of the five seasons under consideration and indeed energy use was highest in this season, but the change over time is likely to be confounded by project interventions in that and subsequent seasons. In the absence of a control group, we cannot be completely certain, but it seems likely that the reduced energy emissions are driven by a combination of more favorable rainfall and project interventions designed to reduce water use. We conclude this because the reduction in energy emissions remains significant from the 2017/18 to 2018/19 seasons, both of which were dry.

4.1.2 Carbon emissions in relation to yield and level of diversification.

CO₂e emissions per unit coffee vary significantly across groups of farmers with different yield levels. Farmers with yields of less than 1,250 kg GBE/ha have a five-year average emission of 2.50 Mt CO₂e /Mt GBE versus 1.01 Mt CO₂e/Mt GBE among farmers with yields in excess of 3,500 kg/ha. This is driven largely by over-application of nitrogen by less productive farmers. Monocrop farmers emit significantly higher volumes of GHGs per unit coffee than medium and highly diversified farmers in the two most recent seasons, and also on a total emissions per ha basis.

To analyze emissions by yield level we would ideally assign farmers to quintiles of yield, such that each yield group contains approximately 20 percent of the farmers in it. This works well in a single season, but as yields differ across season, each season and yield quintile combination would have different yield levels associated with it. This would make comparing yield quintiles and their emissions over time impossible. We therefore used fixed yield level values for each yield group, such that we have at least 30 farmers in any given yield group in a season and a reasonable balanced number of observations within each season ([Table 8](#)).

Table 8: Sample size by yield group and season

		Season				
		2015/16	2016/17	2017/18	2018/19	2019/20
Yield Group (kg GBE/ha)	100$x\leq 1,250$	70	142	226	795	150
	1,250$x\leq 1,750$	203	122	183	726	116
	1,750$x\leq 2,500$	281	265	342	1,858	299
	2,500$x\leq 3,500$	210	679	232	2,625	714
	3,500$x\leq 7,000$	31	492	132	1,834	1,709

We then analyze emissions from fertilizer and energy across yield groups and seasons ([Figure 6](#)).

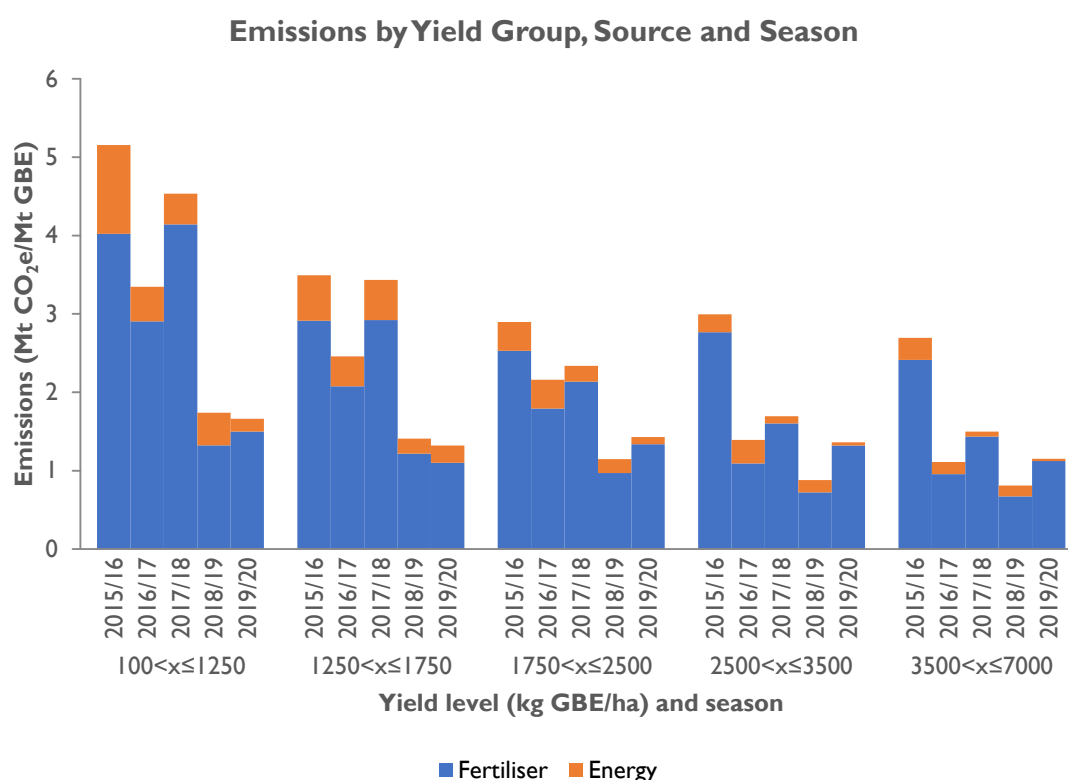


Figure 6: Emissions by yield group and source and season

We find that farmers in the two highest yield groups whose yields range from 2.5 to 3.5 and 3.5 to 7.0 Mt GBE/ha have significantly lower ($p=0.05$) emission levels per Mt GBE produced than farmers in the lowest yield group for every season. Among the highest yield group total emissions in the 2019/20 season came in at 1.15 Mt CO₂e/Mt GBE compared to 1.66 Mt CO₂e/Mt GBE for farmers in the lowest yield group. In absolute terms, i.e. emissions per ha, the most productive segments emit more, but as they are spread over a larger coffee volume, they display a more favorable carbon efficiency compared to farmers in the lower yield groups.

We do find strong seasonal variations, especially the 2018/19 season's lower fertilizer application levels across all yield groups. To even out seasonal effects, we check for significant differences between the five-season average emissions of each yield group (Figure 7).

In this analysis, we find no significant differences between all groups. **This indicates that high(er) yield levels in Vietnam are not necessarily associated with higher emissions per unit coffee.** Further analysis show this is because farmers in the lower yield groups over-apply fertilizer relative to their yield level (Figure 8). Their N application per ha is a factor 1.6 lower than that of farmers in the highest yield group (266 kg/ha versus 437), while their yields are a factor 4.8 lower (0.84 Mt GBE/ha versus 4.10).

The difference in N application per Mt GBE between groups is significant ($p=0.05$) across all groups. The differences in N application per ha are not significant between any of the three mid-level yield groups; all other comparisons are significantly different (Table 9).

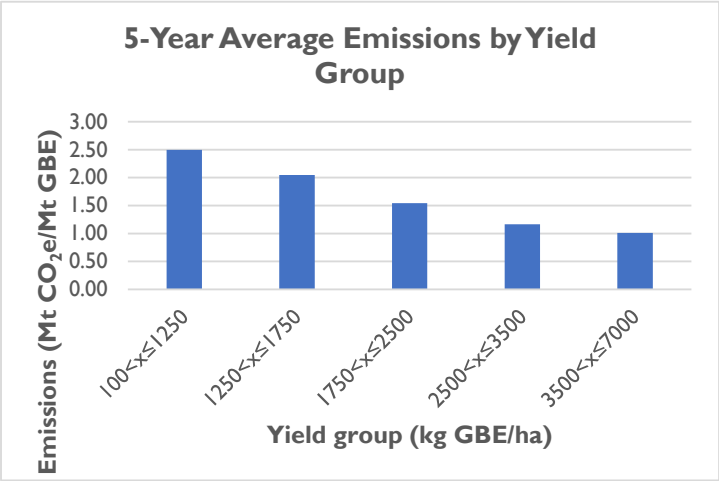


Figure 7: 5-year average emissions (Mt CO₂e/ Mt GBE) by yield group

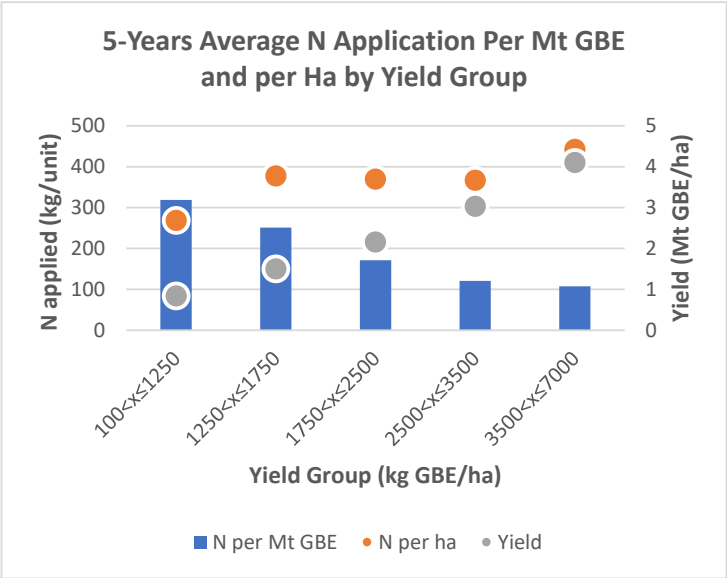


Figure 8: 5-year average nitrogen application in kg per Mt GBE by yield group

Table 9: Post-hoc comparisons of nitrogen application in kg per Mt GBE by yield group (yield in kg GBE/ha) using Tukey's HSD. Mean difference shown. Asterisks indicates the mean difference is significant at the 0.05 level.

	Yield Group Base (kg GBE/ha)	Yield Group (difference from base)				
		100<x≤ 1,250	1,250<x≤ 1,750	1,750<x≤ 2,500	2,500<x≤ 3,500	3,500<x≤ 7,000
N use (kg/Mt GBE)	100<x≤1,250	-	-69*	-148*	-197*	-209*
	1,250<x≤1,750		-	-79*	-128*	-140*
	1,750<x≤2,500			-	-49*	-61*
	2,500<x≤3,500					-12
	3,500<x≤7,000					-

Although all farmers in the sample grow coffee, their farming systems can differ. We apply a distinction between farmers based on the level of diversification of tree species on the farm. We assign farmers to the group 'monocrop' if they have less than 15 percent of non-coffee trees on their coffee farm; medium-diversified farms if they have between 15 percent and 30 percent non-coffee trees on their farm; and highly diversified if they have 30 percent or more non-coffee trees. Sample sizes across the categories are unbalanced and in the 2015/16 season we have no observations in the medium and highly diversified categories. The most robust comparison we can make is between the 2016/17 and 2018/19 seasons. In other seasons, the sample size in the medium and highly diversified groups is on the low side ([Table 10](#)). Still, where possible we present results for other seasons.

Table 10: Sample size (# of farmers) by level of diversification and season

		Season				
		2015/16	2016/17	2017/18	2018/19	2019/20
Group	Monocrop	797	1,177	1,003	4,832	2,868
	Medium-diversified	0	156	29	1,498	36
	Highly diversified	0	412	100	1,946	107

After assigning farmers to level of diversification groups, we analyzed emissions by source and season ([Figure 9](#)).

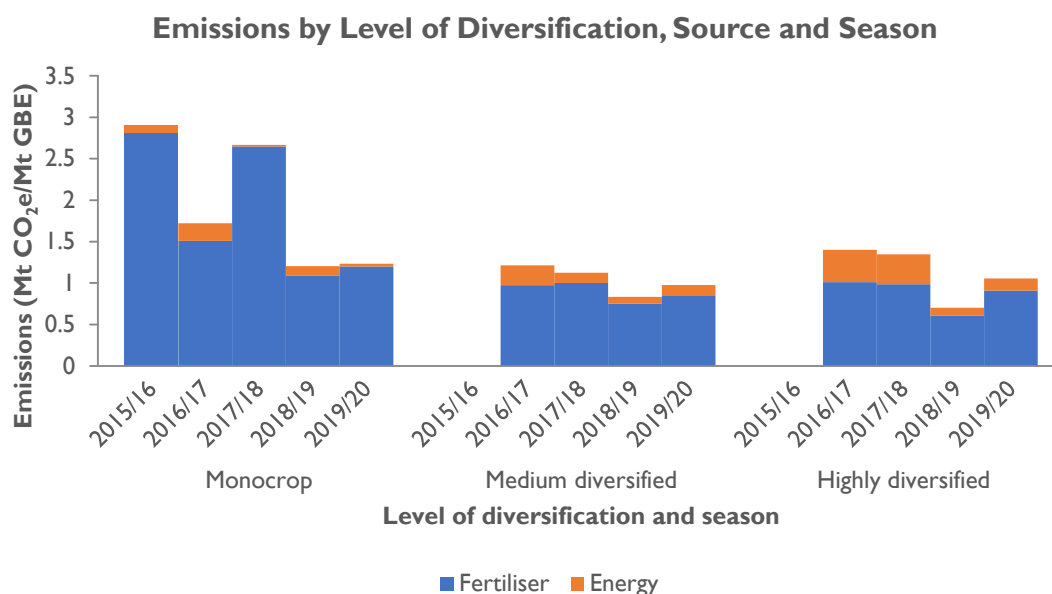


Figure 9: Emissions in Mt CO₂e/Mt GBE by source level of diversification and season

Emission levels for monocrop farmers were at 1.72 Mt CO₂e/Mt GBE in the 2016/17 season, significantly higher ($p=0.05$) than that for farmers in the medium-diversified category (1.21 Mt CO₂e/Mt GBE). The emission level among highly diversified farmers at 1.40 Mt CO₂e/Mt GBE is not significantly different from those among the other two groups. All groups show a reduction of emissions in 2018/19 compared to 2016/17. This change is strongest among the highly diversified farmers, whose average emissions went down by 50 percent. Among monocrop and medium-diversified farms, the reductions were 30 percent and 31 percent, respectively. Consequently, emission levels among all groups were significantly different from one another in 2018/19 (Table 11).

Table 11: Post-hoc comparisons of CO₂e emissions in Mt CO₂e/Mt GBE by level of diversification within seasons using Tukey's HSD. Means are shown. Letters indicate significant differences between levels of diversification within a season at the level of $p=0.05$

Level of diversification	Season				
	2015/16	2016/17	2017/18	2018/19	2019/20
Monocrop	2.90	1.72 ^a	2.67 ^a	1.20 ^a	1.23 ^a
Medium-diversified	-	1.21	1.12	0.83 ^b	0.98
Highly diversified	-	1.40	1.35	0.70 ^c	1.05

We also find that for the four seasons in which we have data on all levels of diversification, i.e. from 2016/17 to 2019/20, emissions among monocrop farmers are significantly higher. The differences we find in the emissions assigned to coffee display a somewhat similar pattern when we review total emissions per ha, i.e. the sum of emissions assigned to coffee and those assigned to other crops, by level of diversification (Table 12).

Table 12: Post-hoc comparisons of total CO₂e emissions in Mt CO₂e/ha by level of diversification within seasons using Tukey's HSD. Means are shown. Letters indicate significant differences between levels of diversification within a season at the level of p=0.05

Level of diversification	Season				
	2015/16	2016/17	2017/18	2018/19	2019/20
Monocrop	4.35	3.46	3.83	2.79 ^a	4.48 ^a
Medium-diversified	No data	3.34	2.92	2.23 ^b	2.72
Highly diversified	No data	3.42	2.59	2.02 ^c	2.57

The difference in emissions per ha was not significant in the 2016/17 and 2017/18 season, but in the following seasons, the pattern is identical to difference in emission per Mt GBE. **On a per ha basis, monocrop farmers emit significantly higher volumes of GHG.** Although energy use is higher in most seasons among highly diversified farmers (Figure 9), monocrop farmers emit significantly higher volumes per ha. **Much of this difference is driven by significantly higher (p=0.05) fertilizer application volumes by monocrop farmers, specifically their nitrogen applications, which contribute most to the fertilizer-related emissions (Figure 10).**

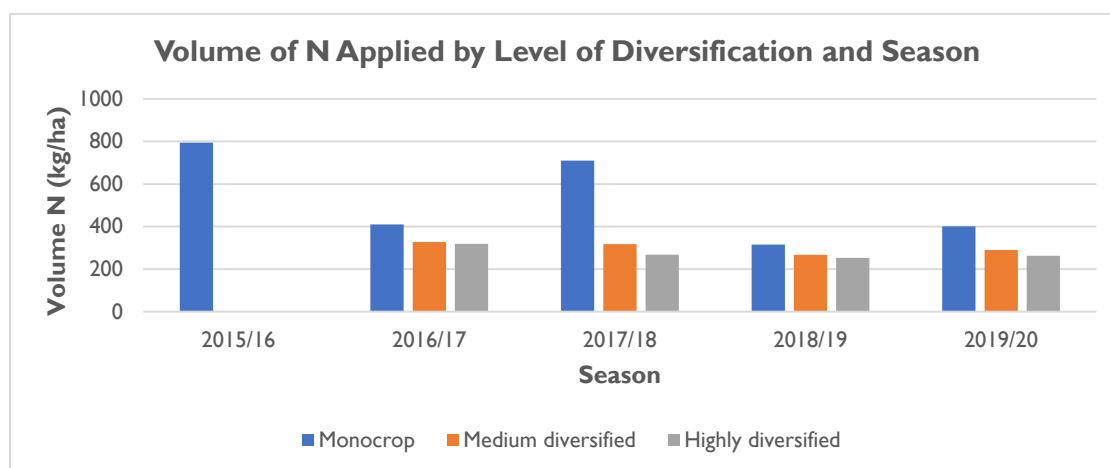


Figure 10: Nitrogen application level in kg/ha single element by level of diversification and season.

4.1.3 Changes in emissions and yields by level of diversification

Coffee yields over time are much more volatile on monocrop farms, yet their long-run average yield is significantly higher than that of medium-diversified farms, which in turn is higher than that of highly diversified farms. Emissions have gone down significantly from 2016/17 to 2018/19 and 2019/20, irrespective of the level of diversification. This may, in part, be driven by declining coffee prices over the same time frame.

Using the level of diversification classification from the previous section, we analyze how yields and emissions have changed over time (Figure 11).

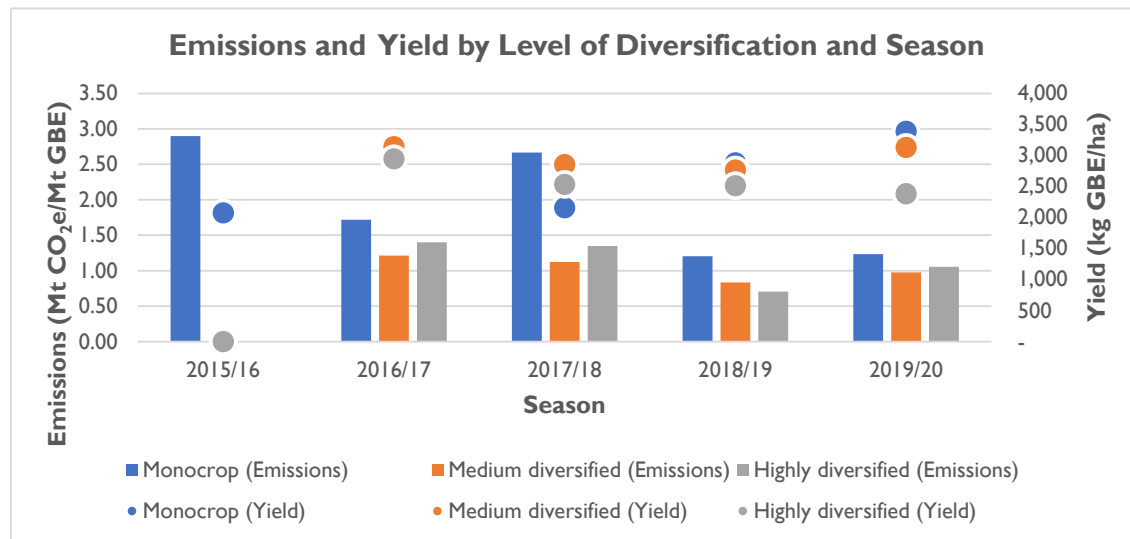


Figure 11: Emissions in Mt CO₂e/Mt GBE and yield in kg GBE/ha by level of diversification and season.

If we only consider the two seasons for which we have a sufficient number of farmers in the diversified categories, i.e. the 2016/17 and 2018/19 seasons, we find that yields have decreased across all categories of farmers. Among monocrop farmers, yield dropped by 307 kg GBE/ha from 3,190 to 2,883 kg GBE/ha. Among medium-diversified farmers, the drop was comparable from 3,143 to 2,767 kg GBE/ha. The drop was stronger among highly diversified farmers who saw their yields reduce by 432 kg GBE/ha from 2,947 to 2,515 kg GBE/ha.

Considering all seasons for which data is available, we find yield levels have recovered among the monocrop and medium-diversified farmers in the 2019/20 season, the yield levels among the highly diversified continue to linger at a significantly lower level ($p=0.05$). Visually, the yield development across the categories over time appears to follow a similar pattern, but the significance of change over time *within* each category is markedly different (Table 13).

Table 13: Post-hoc comparisons of change in yield within each level of diversification over time using Tukey's HSD. Mean difference on previous season shown. * indicates the mean difference is significant at the 0.05 level.

Level of diversification	Season (change on previous)				
	2015/16	2016/17	2017/18	2018/19	2019/20
Monocrop	-	+1,115*	-1,003*	+726*	+509*
Medium-diversified	-	-	-288	-88	+363
Highly diversified	-	-	-411	-20	-130

Table 13 shows that yields among the monocrop farmers are much more volatile. Among farmers in this category, every season's yield is significantly different ($p=0.05$) from the season before that. Not shown in the table, but also present, are significant differences between each pairwise seasonal comparison within this group. Farms in the medium and highly diversified categories do not display this behavior and yields on those farms are much more stable. There appears to be a trade-off between potentially achieving higher yields through monocropping when weather/climate is favorable. Agroforestry might not achieve the same highs under optimal conditions, because space is taken up by other trees and coffee trees receive less flower-inducing sun light exposure. **A benefit of more diversified farms is more resilient yield levels under less optimal weather/climate conditions, reducing vulnerability for changing and/or adverse weather.** As weather conditions are anticipated to become less predictable in the future this could be an important consideration for farmers deciding whether to diversify or not. Despite greater volatility, the long-run five-year average yield among monocrop farmers is significantly higher ($p=0.05$) than that of medium-diversified farms. Medium-diversified farms show significantly higher long-run yields compared to highly diversified farms (Table 14). The difference in long-term yield levels remains significant when we control for location (province) and the year the farm was established.

Table 14: Post-hoc comparisons of 5-year average yield (kg GBE/ha) by level of diversification using Tukey's HSD. Mean values shown. Letters indicate the mean difference is significant at the 0.05 level.

Level of diversification	5-year average yield
Monocrop	2,921 ^a
Medium-diversified	2,788 ^b
Highly diversified	2,625 ^c

Significant differences between level of diversification categories are found in the 2017/18 season when yields on monocrop farms were significantly lower than those among farmers in the other two categories. During the 2018/19 and 2019/20 seasons, all yield differences between all diversification categories were significant ($p=0.05$) and monocrop farmers outperformed farmers in the other categories.

Coffee prices over this same timeframe were on a downward trajectory. It could well be that the highly diversified farmers, who tend to have a more diversified income base, made a conscious decision to pay less attention to coffee in the 2018/19 and 2019/20 season in favor of other crops they grow such as pepper, durian and avocado.

This may help explain why emissions at all levels of diversification are significantly lower ($p=0.05$) in 2018/19 and 2019/20 than in the 2016/17 season. When we plot the change in emissions on previous season by level of diversification, we find greater swings among the monocrop farmers. In seasons where yields on monocrop farms increase, emissions trend downwards and vice versa (figure 12). What this indicates is that investments in fertilizer do not closely follow the expected yield. Emission profiles among monocrop farmers would probably be lower if they adjusted their fertilizer application levels to the expected yield.

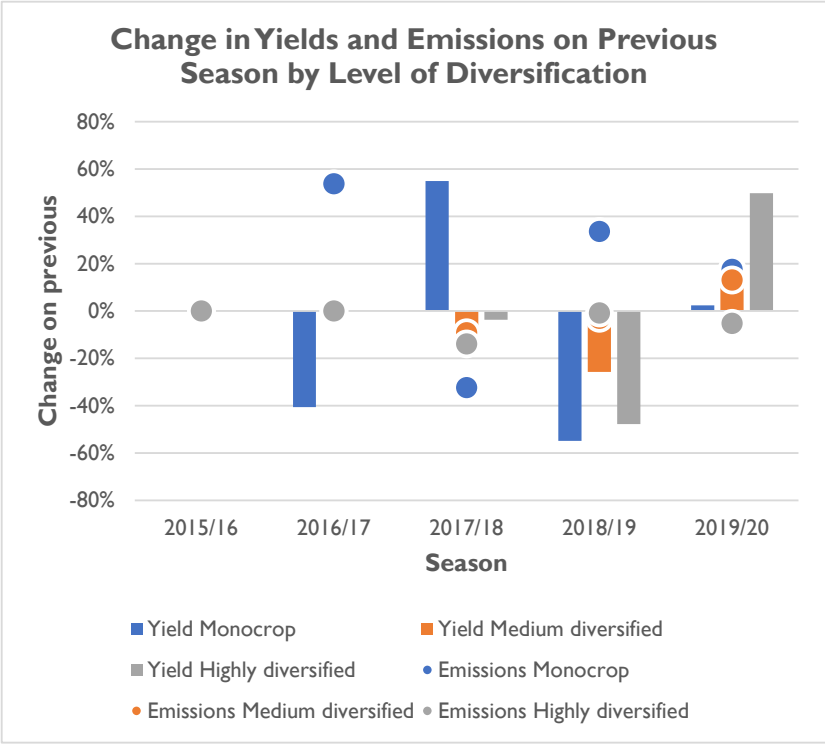


Figure 12: Change in emissions on previous season by level of diversification

4.1.4 Geographical changes in emissions over time

The three provinces for which we have data on emissions over time, show diverging patterns. Emissions in Dak Lak have reduced significantly from 2016/17 to 2018/19 from 1.74 Mt CO₂e/Mt GBE to 0.86 Mt CO₂e/Mt GBE. In Lam Dong emissions show a similar trend, moving from 1.26 Mt CO₂e/Mt GBE to 0.92 Mt CO₂e/Mt GBE in the same time frame. Gia Lai sees a significant increase from 1.59 to 1.85 Mt CO₂e/Mt GBE. At district level, increases in emissions are predominantly found in Lam Dong province.

We do not have data on all provinces in all seasons. While we can show the emission level for all geographies and seasons for which data is available, our ability to analyze change over time is limited to the change from 2016/17 to 2018/19. In those two seasons we have the best geographical coverage. Dak Nong cannot be included, as there we only have data for the 2018/19 season. At first glance, we see three diverging trends across the four provinces (Figure 13).

Emissions in Dak Lak went down from 1.74 Mt CO₂e/Mt GBE in 2016/17 to 0.86 in 2018/19. This reduction is significant at $p=0.05$. In contrast to Dak Lak, the changes in Gia Lai, where company projects have been active for shorter durations of time, show a significant increase in emissions from the 2016/17 season. In Lam Dong the situation has also improved, with emissions decreasing from 1.26 Mt CO₂e/Mt GBE to 0.92 Mt CO₂e/Mt GBE. Data in Lam Dong shows greater swings in emissions during the first four seasons stabilizing, for now, at a lower level in 2019/20. This is related to greater yield swings from season to season as the share of monocrop farmers in our sample is close to 100 percent in that province.

Using the same timeframe, but looking at district level change, shows how provincial developments over time hide strong regional variations within provinces (Figure 14). Out of the 24 districts in the sample, we have data for 11 that cover both seasons we analyze.

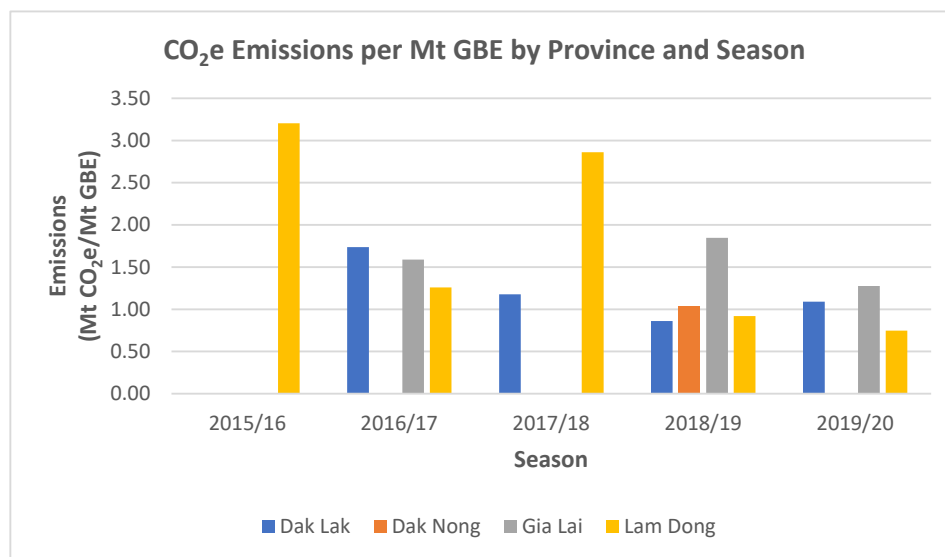


Figure 13: Emissions in Mt CO₂e/Mt GBE by province and season. Lighter colored data points are shown for completeness sake but not included in analyzing change over time.

In Gia Lai province we have an imbalance on the panel data, the number of farmers in the sample is greater in 2018/19 and they are found in several districts. A subgroup of Gia Lai farmers in Dak Doa district show a non-significant decrease ($p=0.05$) in emissions of 0.12 Mt CO₂e/Mt GBE, but at provincial level emissions trend upwards.

Dak Lak has better data coverage. Four out of the five districts for which we have data show a decrease in emissions by up to 1.21 Mt CO₂e/Mt GBE in Buon Don district. Krong Buk district (including Buon Ho town) is the odd one out; here emissions increased as a result of a combination of lower yields and higher nitrogen applications. A general trend in the districts in Dak Lak with lower emissions per unit coffee is that yields have decreased from just over 3,000 kg GBE/ha in 2016/17 to 2,724 kg GBE/ha in 2018/19. Over the same time frame, nitrogen applications have also dropped by more than enough to offset the yield reduction. Had investment levels stayed the same, then emissions per unit coffee would have increased significantly.

But as average nitrogen application reduction was greater than the yield reduction from just over 177 kg/Mt GBE to 111 kg/Mt GBE in 2018/19, the emissions per unit coffee decreased significantly ($p=0.05$), despite lower yields. In the absence of a control group we are uncertain to what degree this change is driven by lower coffee prices or by project interventions.

In Lam Dong, performance is more mixed. In Di Linh district, both the largest production area and the district where several partners have been active since 2015, we find positive developments with significantly lower ($p=0.05$) emissions per unit coffee in 2018/19. Yields went down, but nitrogen applications also decreased over this time frame from 85 kg N/Mt GBE to 66 kg. Energy-related emissions increased over the same timeframe, but not by enough to push overall emissions upwards. Bao Lam district in Lam Dong demonstrated a stronger yield decrease without an associated reduction in fertilizer applications, resulting in rising emissions per unit coffee. This also applies to the Arabica areas of Da Lat City in the North-West of Lam Dong province.



Figure 14: Change in CO₂e emissions in Mt CO₂e/Mt GBE by district from 2016/17 to 2018/19. Color scale shows direction of change with greens indicating reduced emissions and red shades increases

4.2 Carbon stocks and sequestration

In this section we look into carbon stocks by level of diversification, how these have changed over time and what geographical patterns we can identify.

4.2.1 Carbon stocks by level of diversification

Monocrop farms, which tend to be older, had carbon stocks of 41.6 Mt CO₂e/ha in 2016/17, significantly more than highly diversified farms whose tree stocks are larger but more recently planted. As coffee is being replaced, the sample stabilizes and tree stocks on more diversified farms mature, carbon stocks on medium and highly diversified farms (>42 Mt CO₂e/ha) outstrip that of monocrop farms (34.0 Mt CO₂e/ha) in 2019/20 by a significant margin.

The sample of farmers in different categories of diversification ([Table 10](#)) is used to analyze carbon stocks. We calculate carbon stocks by estimating Above Ground Biomass of the trees on the farm. We do this by considering the year farmers say trees were planted, in which number, and an allometric model with species-dependent parameters that describe how biomass is expected to change over time. In combination with the CO₂e fraction in the biomass we can estimate the carbon stocks expressed in Mt CO₂e/ha ([Figure 15](#)).

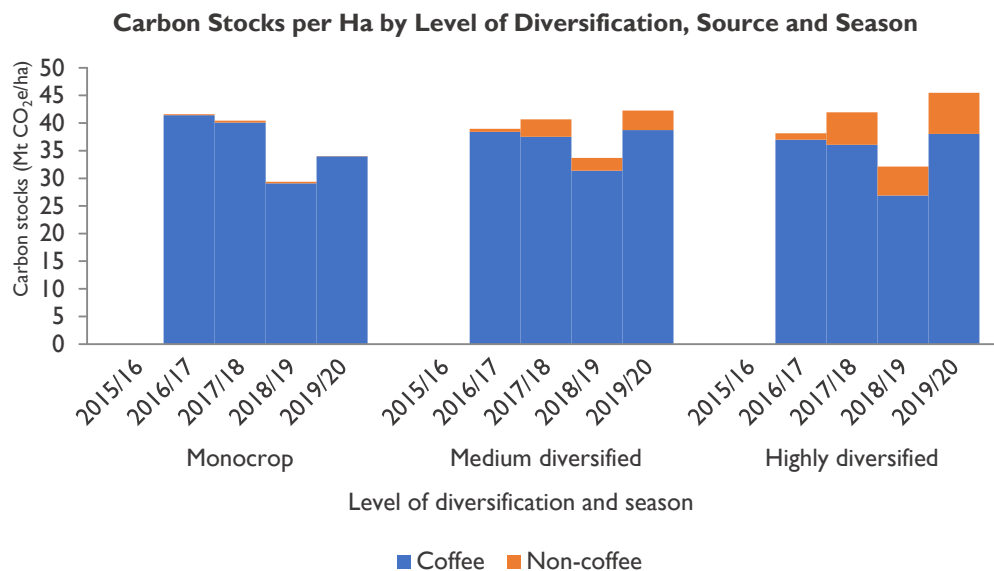


Figure 15: Carbon stocks in Mt CO₂e/ha by season and level of diversification

The four-year average carbon stocks (there is no tree stock data available for 2015/16) across all levels of diversification comes at 33.0 Mt CO₂e/ha. We do not have tree stock data for every farmer in the sample in every year, neither is every farmer with tree stock data present in the sample every year. This imbalance may explain part of the change we observe. When we review the segment of farmers with complete data in 2016/17 and 2018/19, the situation is more stable but overall trends by level of diversification are similar.

A further impediment to analysis, especially on medium and highly diversified farms is that not all partners have recorded data for species that do not directly yield income. On farms that grow pepper, *Cassia spec.* is often used for pepper vines to grow up against, but as the *Cassia spec.* does not provide a direct source of income, their numbers and year of planting are not always recorded. We applied two assumptions to deal with this: i) 70 percent of pepper vines are growing on cassia trees (the other 30 percent on concrete or wooden poles), and ii) we assume that the cassia is planted two years prior to pepper vines.

With these assumptions, carbon stocks were 41.6 Mt CO₂e/ha on monocrop farms, versus 38.9 and 38.1 Mt CO₂e/ha on medium and highly diversified farms, respectively, in 2016/17. The difference in that season between the monocrop and highly diversified farms is significant (p=0.05) (*Table 15*).

Table 15: Post-hoc comparisons of carbon stocks in Mt CO₂e/ha between levels of diversification within each season using Tukey's HSD. Means are shown. Letters indicate the mean difference is significant at the 0.05 level.

Level of diversification	Season				
	2015/16	2016/17	2017/18	2018/19	2019/20
Monocrop	No data	41.6 ^a	40.4	29.4 ^a	34.0 ^a
Medium-diversified	No data	38.9 ^{ab}	40.7	33.7 ^b	42.2 ^b
Highly diversified	No data	38.2 ^b	41.9	32.1 ^c	45.5 ^c

Stocks drop in 2018/19 as a result of inflow of new farmers into the sample. In the season thereafter, replanting efforts on monocrop farms start to show their effect, when monocrop farms no longer outperform farms in the other two categories. As newly planted trees have established themselves, the stocks are moving in the direction one would expect, with medium and highly diversified farms showing significantly higher carbon stocks (42.2 and 45.5 Mt CO₂e/ha respectively) than monocrop farms (34.0 Mt CO₂e/ha) in 2019/20. One might expect a larger difference in stocks between highly diversified and medium-diversified farms, but the first grows much more pepper, which sequesters less carbon, compared to larger woody species such as avocado and durian, which are more prevalent on medium-diversified farms.

Changes over time in average carbon stocks tend to be significant, but only the highly diversified farms have significantly higher stocks in 2019/20 than they had in 2016/17 (

Table 16).

Table 16: Post-hoc comparisons of change in carbon stocks in Mt CO₂e/ha within levels of diversification between each season using Tukey's HSD. Mean differences are shown. Asterisks indicate if differences are significant at the p=0.05 level.

Level of diversification	Base	Season (change on base)			
		2016/17	2017/18	2018/19	2019/20
Monocrop	2016/17	-	-1.15	-12.2*	-7.6*
	2017/18		-	-11.1*	-6.5*
	2018/19			-	-4.6*
	2019/20				-
Medium-diversified	2016/17	-	+1.7	+5.2	+3.3
	2017/18		-	-7.0*	+1.6
	2018/19			-	+8.5*
	2019/20				-
Highly diversified	2016/17	-	+3.8*	-6.0*	+7.3*
	2017/18		-	-9.8*	+3.6*
	2018/19			-	+13.4*
	2019/20				-

In the most recent season on monocrop farms, stocks are significantly lower than they were in 2016/17, while stocks appear stable at the medium-diversified farms.

4.2.2 Changes in carbon stocks by locations

Carbon stocks tend to be stable on more mature farms, but here we find a strong dip in stocks in the 2018/19 season from around the 40 Mt CO₂e/ha mark to around 32 Mt CO₂e/ha. This is driven by inflow of new farmers into the sample and replanting activities. We find no significant difference in carbon stocks between levels of diversification, although we expect that to materialize over time as much planting has been recent. Stock levels in 2019/20 have recovered to statistically higher levels in Dak Lak compared to 2016/17 and appear to be on track to do so next season in Lam Dong.

The sample by province is skewed by the absence of detailed tree stock data for Dak Nong and Gia Lai province. Our models to estimate carbon stocks rely on tree stock numbers, species, and the years in which batches of tree species were planted. This data is only available for a segment of farmers in Dak Lak and Lam Dong. Plotting tree stock data reveals a number of patterns (Figure 16)

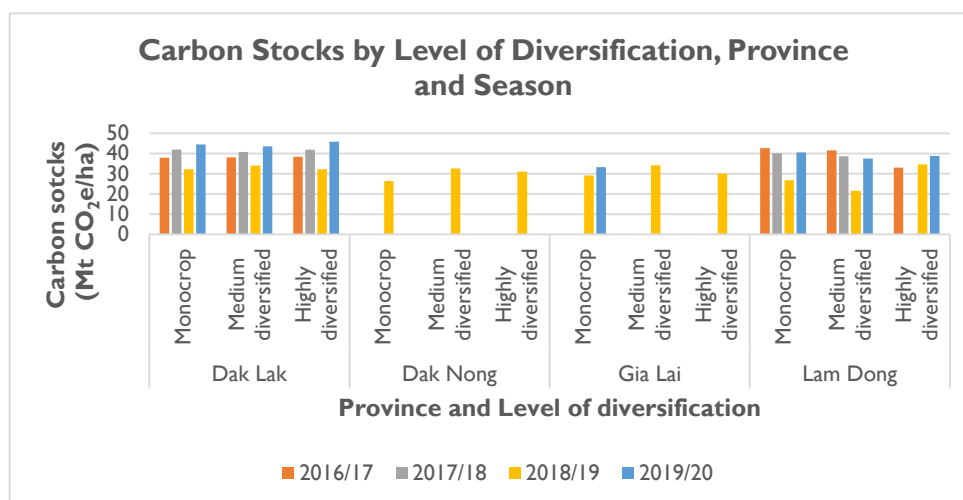


Figure 16: Carbon stocks in Mt CO₂e/ha by level of diversification, season and province.

First of all, we see a dip in stocks in the 2018/19 season, in part this is because of inflow of new farmers into the sample, but also likely as a result of farmers renovating and rejuvenating farms after a period of sustained lower prices. We also observe significant planting of new trees, the effects of which contribute to the stock recovery in 2019/20. Second, we observe that highly diversified farms are not showing significantly higher carbon stocks than monocrop farms. In part this is because their coffee planting density is significantly lower ($p=0.05$) at a five-year average of 857 coffee trees/ha versus monocrop farms that grow 1,007 trees/ha. Additionally, highly diversified farms rely on pepper, which does not sequester as much carbon as non-coffee trees (avocado and durian) more common on medium-diversified farms.

A further explanation could be the finding of CIAT (2018) which indicates that diameter at 15 cm above the ground level of coffee on highly diversified farms are smaller, resulting less biomass per coffee tree grown. Stock changes over time by province and level of diversification show a significant decrease ($p=0.05$) across all province and level of diversification categories when we observe the seasons for which we have most data, i.e. from 2016/17 to 2018/19, except for highly diversified farms in Lam Dong. With the recovery in stocks we observe in the 2019/20 season, all but one group is back at statistically similar levels ($p=0.05$) as in 2016/17 (Table 17).

Table 17: Regression co-efficients of seasonal change in carbon stocks where the 2016/17 season is the base season against which others are compared. * denotes significant difference at $p=0.05$.

		Season (change on 2016/17)			
		2016/17	2017/18	2018/19	2019/20
Dak Lak	Monocrop	-	+4.0	-5.7*	+6.5*
	Medium-diversified	-	+2.7	-4.0*	+5.5*
	Highly diversified	-	+3.5*	-6.1*	+7.5*
Lam Dong	Monocrop	-	-2.6	-16.0*	-2.2
	Medium-diversified	-	-3.0	-20.1*	-4.1
	Highly diversified	-	No data	+1.7	+2.4

The province level pattern with more or less consistently lower carbon stocks in 2018/19 when compared to 2016/17 is also found at district level (Figure 17).

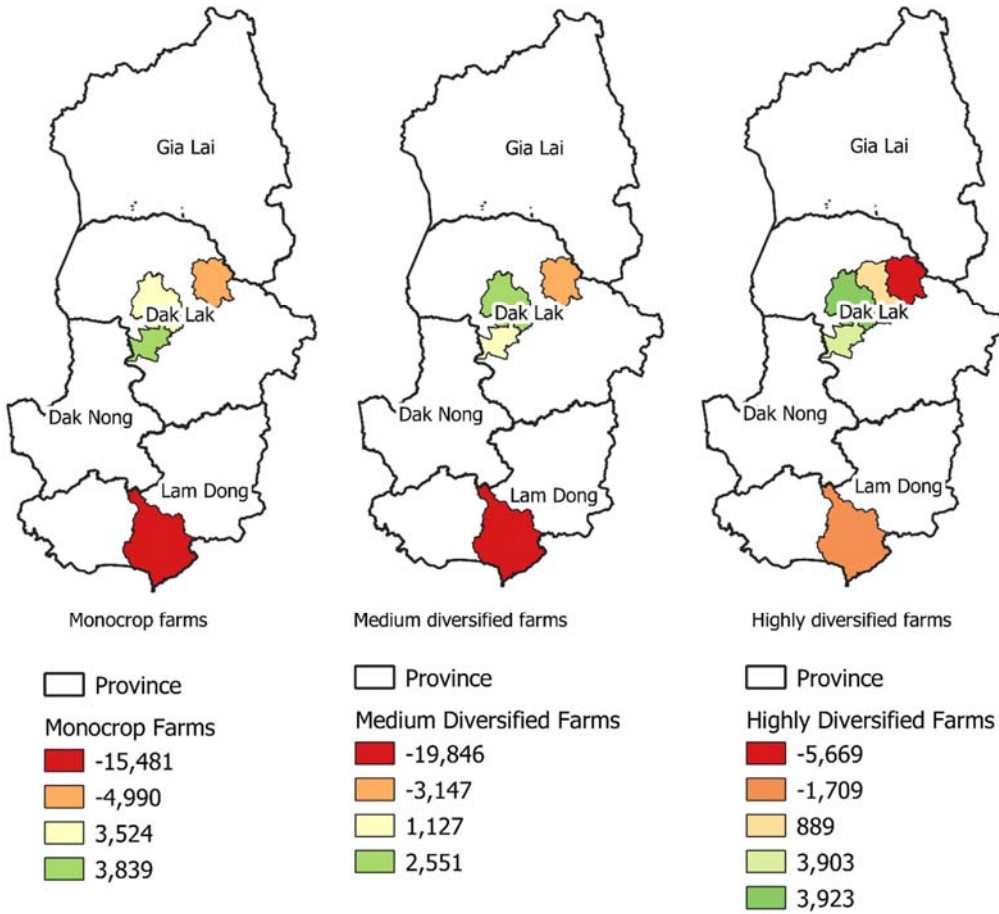


Figure 17: Change in carbon stocks (in Mt CO₂e/ha) from the 2016/17 to the 2018/19 season by level of diversification and district. Note that a discrepancy exists between Table 17 and the map for Lam Dong province as 2016/17 data in the table includes stock values from Bao Lam district, whose stocks were not available for 2018/19 and hence not included here.

In just two of the districts do monocrop farms show a carbon stock increase from 2016/17 to 2018/19. The same applies to medium-diversified farms, with similar trends in the same districts as the monocrop farms, albeit at different levels. Highly diversified farms show only an increase in three of the four districts in Dak Lak, but nowhere else. The change in stocks from one season to the next is the rate of carbon sequestration. This value can be negative if the CO₂e volume contained in the trees that are removed outweighs the amount built up in stocks in the remaining trees. Or as is largely the case here, if the inflow of new farmers into the sample have lower tree stocks, younger trees or a combination thereof, there is lower average stock levels from one season to the next.

4.3 Carbon footprint

In this section we review the change of carbon footprint over time between levels of diversification and across geographies. We also compare our findings with literature and project our outcomes to sector level.

4.3.1 Emissions, sequestration and footprint per ha and by level of diversification

The carbon footprint on a per ha basis on highly diversified farms is significantly lower than that on monocrop farms. In part this is because of higher carbon sequestration rates, but more importantly by lower emissions. Across the three levels of diversification, we observe a downward trend in carbon footprints per ha.

The rate of carbon sequestration is calculated for each farm by subtracting the ending stocks of a particular season by the ending stocks of the preceding season. Since 2016/17 is the first season for which we can reliably calculate carbon stocks, the 2017/18 season is the first one for which we can calculate the rate of sequestration. For this reason, the analysis in this section covers the period from 2017/18 to 2019/20. The footprint (or net emissions) is calculated by subtracting sequestration from emissions. A negative footprint value indicates that more CO₂e is removed from the air than is emitted during the production process and vice versa. Emission values are used from farmers for whom we can also calculate the rate of sequestration. This is a sub-sample of the farmers for whom we could calculate the emissions per unit GBE in section 0.

We first review emissions (all emissions, not just the share that can be assigned to coffee), sequestration, and the carbon footprint per ha. As we found in section 0, the emissions on monocrop farms show greater fluctuations than those on the other types of farms. Clearly, this is not only driven by greater yield volatility ([Figure 18](#)).

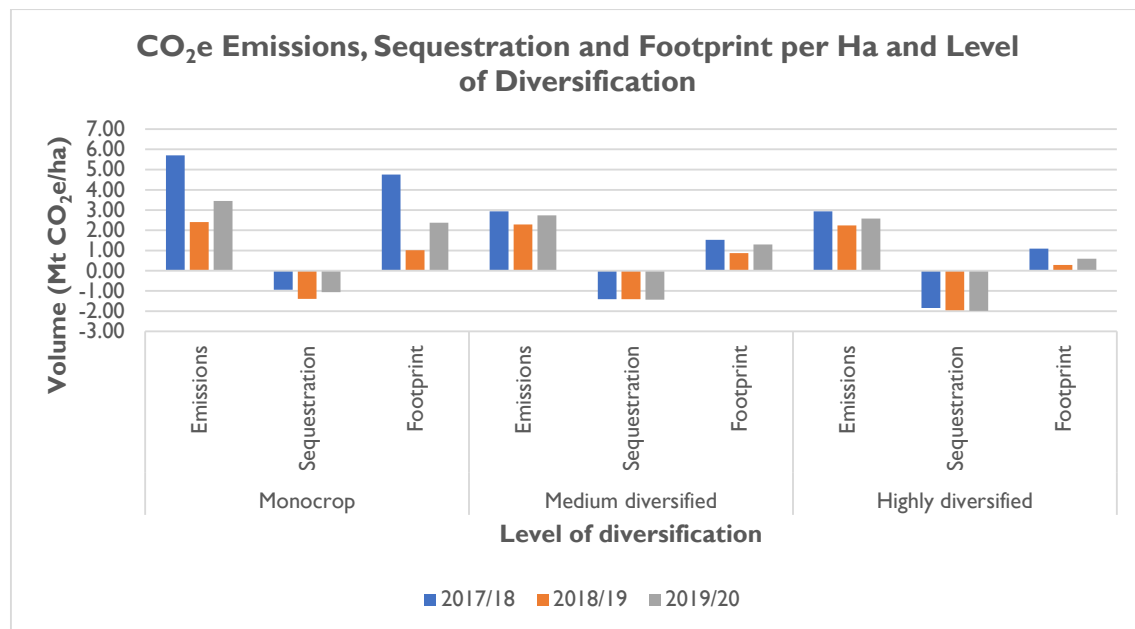


Figure 18: Emissions, sequestration, and footprint per ha by level of diversification and season

This reveals that the footprint per ha on highly diversified farms is consistently lower than on monocrop and medium-diversified farms across the three seasons.

All levels of diversification display a similar downward trend, and among both the monocrop and highly diversified farms, the footprint in 2019/20 has decreased significantly ($p=0.05$) compared to 2016/17. On highly diversified farms the rate of sequestration is between 1.85 to 1.96 Mt CO₂e/ha, versus between 0.96 and 1.37 Mt CO₂e/ha on monocrop farms, resulting in net footprints of between 0.28 and 1.09 Mt CO₂e/ha and 1.01 and 4.83 Mt CO₂e/ha, respectively. Given that the rate of sequestration is fairly stable, unless farmers decide to conduct large-scale rejuvenation on their farms by uprooting and replacing old coffee trees, the large determinant of the footprint is farmers' investment decisions. For example, in 2018/19, average emissions on monocrop farms decreased by a factor of 2.4 as a result of lower fertilizer and energy expenditures.

4.3.2 Share of farmers and emission-sequestration balance by level of diversification

Nearly one-third of the highly diversified farms had a negative carbon footprint in the 2019/20 season. While this share was lower in previous seasons, it was significantly higher when compared to monocrop and medium-diversified farms in each of the seasons. Irrespective of the level of diversification, negative footprint farms spend significantly less on fertilizer, but their yields are also lower.

The average values from the previous section hide much of the variation in footprints. When we analyze the share of farmers across each category that have a negative footprint, even among monocrop farms there is a small group of farmers of up to 10 percent, depending on the season, with negative footprints, meaning they remove more carbon from the air than they emit during production (*Figure 19*).

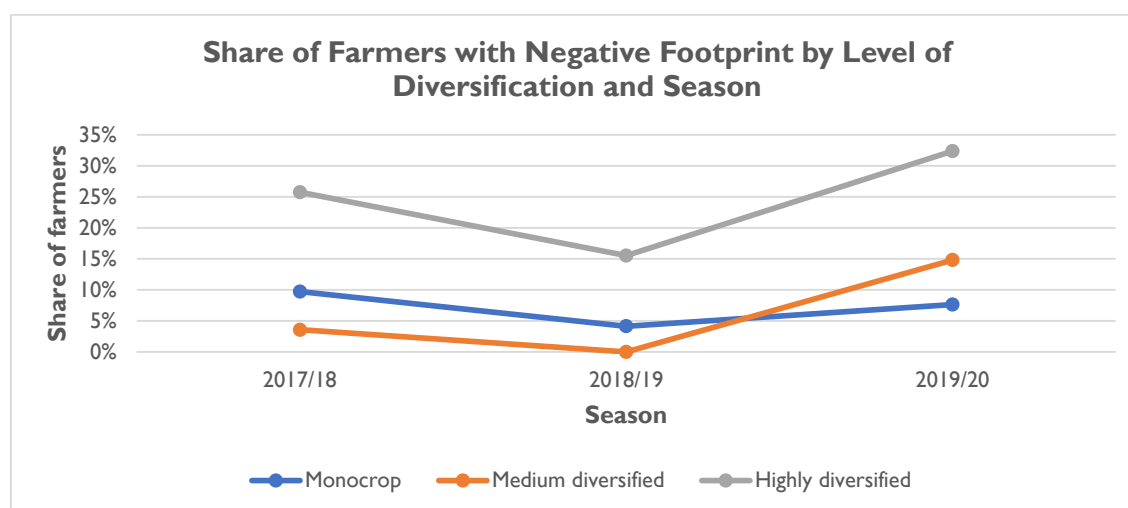


Figure 19: Share of farmers with negative footprints in Mt CO₂e/ha by level of diversification and season.

In each season the share of farmers with a negative carbon footprint is significantly higher ($p=0.05$) on highly diversified farms. Nearly one-third of the highly diversified farms had negative carbon footprints in the 2019/20 season, compared to 8 percent and 15 percent for monocrop and medium-diversified farms, respectively. Although the rate of sequestration is significantly higher on highly diversified farms, this alone is not sufficient to bring a larger group of farmers into negative carbon footprint territory. For this to happen, optimizing fertilizer investment remains imperative (*Figure 20*).

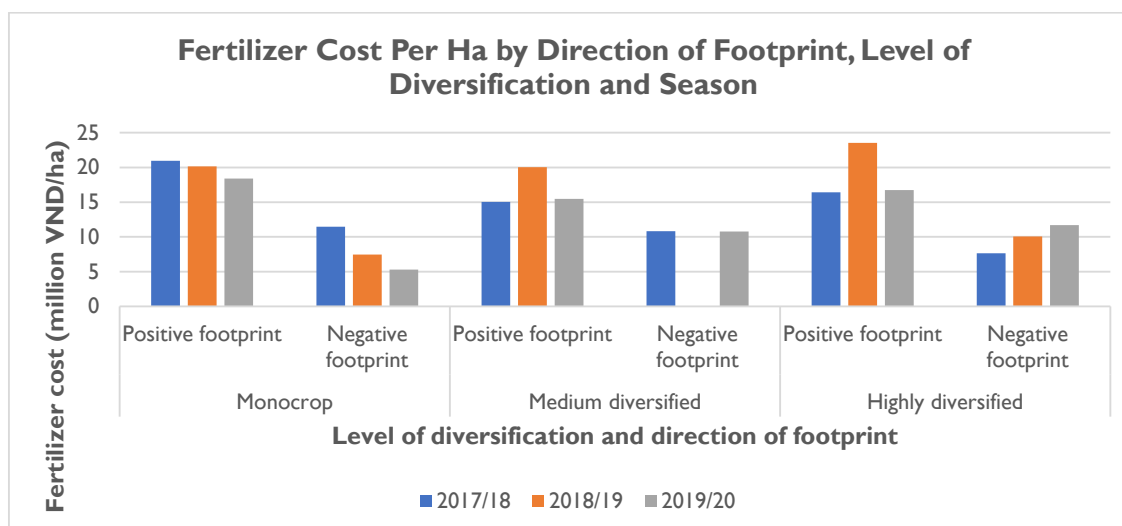


Figure 20: Fertilizer cost per ha by level of diversification, direction of carbon footprint and season

Figure 20 shows how farmers with a negative footprint invest significantly less in fertilizer than their peers within the same diversification group who have positive carbon footprints. On negative footprint farms, fertilizer investment ranges from 5.3 to 11.7 million VND/ha (230 USD to 508 USD), depending on the season and diversification group, whereas among farms with a positive carbon footprint this is at least 15 million VND/ha (652 USD). Just lowering fertilizer investment is probably not going to work; on the negative carbon footprint farms, coffee yields are significantly lower ($p=0.05$) than their peers within the same group of diversification. Optimizing fertilizer investment in combination with planting a suitable mix of non-coffee trees to increase the rate of diversification and hence sequestration is a more suitable trajectory.

4.3.3 Emissions, sequestration, and footprint by level of diversification and geography

By province, the share of farms with negative carbon footprints is highest in Dak Lak at 32 percent of the highly diversified farms. In Lam Dong, such farms are rare and consequently the share of farmers with negative footprints is lower at 14 percent and 16 percent, respectively, for monocrop and medium-diversified farms. Data for this analysis is drawn from a limited number of districts and cannot be considered representative for the wider sector.

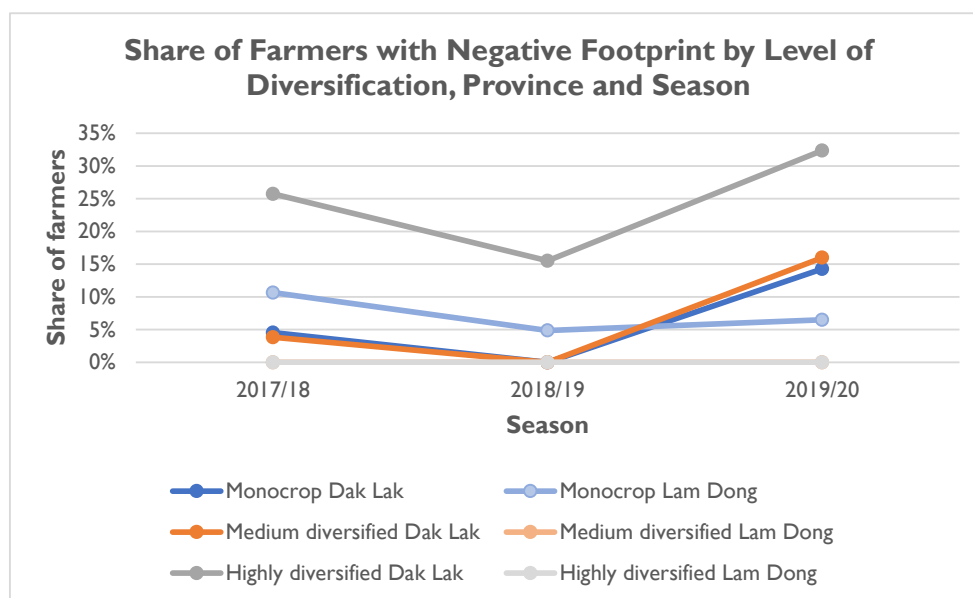


Figure 21: Share of farmers with negative footprint by level of diversification, province, and season

The majority of highly diversified farms are found in Dak Lak province. Consequently, analyzing the share of farmers with negative carbon footprints by level of diversification and province gives a very similar picture to what we found in the previous section (Figure 21). Contrary to the previous section, we do find that within Dak Lak, the share of farmers with negative footprints on monocrop and medium-diversified farms are nearly identical. Still, the differences with Lam Dong province are not very large. In both provinces, the share ranges from 4 percent to 16 percent, half or less than half of what we find on highly diversified farms.

Given limited data availability on tree stocks and years of planting and, consequently, the limited number of carbon footprints we can calculate, the coverage by province is highly skewed with data from only two districts in Dak Lak and a single district in Lam Dong province (Table 18). For the highly diversified category in Lam Dong, we have no observations. It is advisable to take overall and provincial number as indicative of what could be and not of what actually is in excluded geographical areas. Data is not representative enough.

Table 18: Emissions (E), sequestration (S) and Footprint (F) by district, level of diversification and season in Mt CO₂e/ha with post-hoc comparisons of difference in carbon footprint between levels of diversification within districts and seasons using Tukey's HSD. Mean values are shown. Letters indicate if differences are significant at the p=0.05 level

				Season		
				2017/18	2018/19	2019/20
Dak Lak	Buon Ma Thuot	Monocrop	E	2.66	3.05	2.26
			S	-1.18	-1.19	-1.17
			F	1.48	1.87	1.09
		Medium-diversified	E	2.83	3.17	2.31
			S	-1.38	-1.42	-1.42
			F	1.45	1.75	0.90
		Highly diversified	E	2.88	3.62	1.98
			S	-1.64	-1.75	-1.78
			F	1.24^a	1.87	0.19^a
	Cu M'Gar	Monocrop	E	2.67	1.56	2.10
			S	-1.21	-1.19	-1.21
			F	1.45	0.36	0.89
		Medium-diversified	E	3.05	3.15	3.01
			S	-1.48	-1.44	-1.50
			F	1.56	1.71	1.51
		Highly diversified	E	2.96	2.94	2.93
			S	-1.94	-2.05	-2.08
			F	1.03	0.89	0.85
Lam Dong	Di Linh	Monocrop	E	2.98	2.16	0.75
			S	-0.90	-1.43	-1.05
			F	2.08	0.73^a	-0.29^a
		Medium-diversified	E	2.92	3.13	3.03
			S	-1.17	-1.18	-1.20
			F	1.75	1.94	1.83
		Highly diversified	E	No data	No data	3.11
			S	No data	No data	No data
			F	No data	No data	No data

Sequestration rates tend to be higher on more diversified farms, irrespective of district. This applies in particular to Dak Lak province, where we have ample observations in each diversification and season group. Here the footprint values are significantly lower on highly diversified farms in two of the three seasons. The district level breakdown also shows that emissions have reduced in most areas. Only among highly diversified farms in Cu M'Gar and medium-diversified farms in Di Linh did emissions stay stable at a relatively high level of around 3.0 Mt CO₂e/ha.

4.3.4 Comparison footprints with literature

In the coffee sector, most carbon footprint work has focused on Latin America and on Arabica production. Very few benchmarks are available for Robusta coffee. CIAT has done work on Robusta footprints in Vietnam and finds comparable values to our work, albeit from a far smaller sample.

To date, most of the work estimating carbon emissions in coffee production has taken place in Latin America focusing on Arabica coffee. Arabica tends to be wet, or semi-wet processed while Robusta is mostly sun-dried. According to Rikxvoort et al (2014), 57 percent of Arabica-related emissions originate from fermentation and wastewater. Comparing emissions from Arabica and Robusta production systems is not advisable. Robusta coffee, despite its importance for global supply, has received little attention. As a result, not much is known about carbon emissions in Vietnam's coffee production. CIAT conducted a study on a sample of 50 farms in Dak Lak using data for the 2015 season (Nguyen-Duy et al, 2018). In addition to emissions, the study also contains data on Above Ground Biomass and carbon stocks. Tree stock composition in this study aligns with what we found with *Cassia spc.* being the most prevalent non-coffee tree, followed by a mix of avocado and durian. The CIAT study did find much more cashew than we did, but in our experience cashew plantings tend to be fairly localized and not so widespread. The inclusion of cashew is likely due to CIAT's study site. The study found emission values ranging from 3.01 to 7.22 Mt CO₂e/ha, depending on the level of shade and intensiveness of farm management, compared with our slightly lower values of 2.24 to 5.70 Mt CO₂e/ha. CIAT's finding of emissions per unit coffee varies again by use of shade and intensity of management, but ranges from 1.89 to 2.78 Mt CO₂e/Mt GBE; our data indicates a range from 1.22 to 3.21 Mt CO₂e/Mt GBE depending on the season (*Table 19*).

Table 19: Comparison of ranges of emissions, stocks and footprint values from selected studies

	Location, authors and year of publication				
Aspect	This study	Vietnam, Dak Lak Nguyen Duy et al (2018)	Vietnam, Lam Dong Trinh et al (2018)	Uganda Bunn et al (2019)	Thailand Rachawat (2018)
Emissions (Mt CO ₂ e/ha)	2.24-5.70	3.01-7.22			
Emissions (Mt CO ₂ e/Mt GBE)	1.22-3.21	1.89-2.78	0.92-0.95	0.72	
Carbon stocks (Mt CO ₂ e/ha)	29.4-45.5	7.63-26.3 (Mt C) 28.0-96.5			
Footprint (Mt CO ₂ e/ha)	0.28-4.76	-1.5-2.8			
Footprint (Mt CO ₂ e/Mt GBE)		-2.4-1.0			2.0

We have observed significant swings in emissions from one season to the next and significantly higher emissions in the 2015/16 season, making our results comparable to the CIAT study. Similar to our work, CIAT also finds significantly higher carbon stocks for shaded, or in our vernacular, highly diversified farms. CIAT's study found stock values on unshaded farms that range from 7.63 to 12.9 Mt C/ha, which is comparable to the ~40.0 Mt CO₂e/ha we find on mature monocrop farms. Sequestration rates are higher on the farms CIAT investigated, but when we isolate established farms in our sample with mature shade trees the values align. Findings on the carbon footprint are also largely aligned. CIAT found lower footprints among more diversified farms. Their average footprint values were negative for the season under consideration, ranging from -0.4 to -3.2 Mt CO₂e/ha, a bit lower than what we found in later years. For monocrop farms the values are also aligned; CIAT finds 0.8 to 4.6 Mt CO₂e/ha in unshaded systems versus our findings of 1.01 to 4.76 Mt CO₂e/ha.

Trinh et.al. (2018) found somewhat lower emission values of 0.92 to 0.95 Mt CO₂e/Mt GBE in conventional intensive production systems in Tan Ha commune, Lam Dong province on a sample of 42 farmers during the 2017/18 season. About two-thirds of their sample were either organic or moderately intensive conventional producers, so their sample base is rather narrow. Their findings are close to the emission values we see in 2018/19, but only about one-third of what we found in the 2017/18 season (2.61 Mt CO₂e/Mt GBE). Given the high variability we find from one season to the next, we do think that any analysis of footprints should consider multiple years. Indeed this is also prescribed by the now delisted² Product Category Rule for green coffee (Environdec, 2013).

Compared to other Robusta origins, Vietnam's production is likely very carbon-intensive as its farmers are known for their high input use (GroIntelligence, 2016). Uganda, according to Bunn et.al. (2019), has a carbon footprint of 0.72 Mt CO₂e/Mt GBE, but it is unclear from their paper if this footprint covers gross or net emissions (i.e. after deducting sequestration). We suspect this number deals with gross emissions, and the authors estimate Ugandan coffee emissions to be a factor five times lower than Vietnam's, which aligns with our emission values for the 2015/16 season.

Rachawat (2018), investigated Thai Robusta production and arrived at a footprint of 0.40 Mt CO₂e/Mt fresh cherry, assuming a conversion rate of five from fresh cherry to green bean, this equates to 2.0 Mt CO₂e/Mt GBE, not too far off from what we found in Vietnam. The current analysis does come up with somewhat higher footprint values than what we found in earlier work (IDH, 2018), but the earlier work was done on a smaller sample of farmers who were expressly supported to reduce their input use and increase their rate of diversification. The studies we found for Robusta are few, but what was found points in the same direction: **emissions come largely from fertilizer, production can be carbon neutral and neutrality can be achieved by optimizing input use and increasing diversification.**

4.3.5 Projection of emissions for project and sector population and options to reduce them.

Across the various projects of the partners, we estimate that the 14,100 farmers they engage with emit close to 74,000 Mt CO₂e per annum in gross emissions. At sector level in the Central Highlands, we estimate net emissions to be just over 800,000 Mt CO₂e per year. Reducing this can be achieved by increasing diversification, but a more impactful approach would be to optimize nitrogen use.

Although our sample for the sequestration side of the work is not representative for the sector, we find the few other available studies point largely in the same direction. On this basis we model ways to reduce the carbon footprint at the level of project implementation and at sector level in Vietnam.

² A Product Category Rule is valid for a certain period of time to ensure that it is regularly updated. The Green Coffee PCR has not been updated within this interval and is therefore now delisted and no longer considered valid. Still, it remains in our view the most accurate guideline for Green Coffee foot printing and we recommend the coffee sector, e.g. through SCC or GCP to attempt renewal of the registration.

Not all farmers of the 14,100 farmers who participate in the respective projects of the partners are included in our dataset. Across the various projects, 7,100 farmers are located in Dak Lak, 1,000 in Dak Nong, and 3,000 each in Gia Lai and Lam Dong. We project emissions for the entire project population by assigning the population in each province to the three categories of diversification based on the ratio we find for each province. We then apply the average farm size and the three-year average emissions in each category to estimate total emissions by province and across the projects (*Table 20*).

Table 20: Projection of total emissions in Mt CO₂e among project population through level of diversification (MCF=Monocrop farms; MDF=Medium-diversified farm; HDF=Highly diversified farms)

Province	Diversification	Share of farmers (2019/20)	Average farm size (ha)	Estimated total area (ha)	Emissions (Mt CO ₂ e/ha)	Total emissions (Mt CO ₂ e)
Dak Lak	MCF	34.0%	1.44	3,468	2.75	9,550
	MDF	12.9%	1.18	1,080	2.93	3,160
	HDF	53.1%	1.11	4,175	2.92	12,212
Dak Nong	MCF	97.6%	2.08	2,027	2.63	5,330
	MDF	0.0%	No data	No data	No data	No data
	HDF	2.4%	1.15	27	2.63	72
Gia Lai	MCF	99.9%	2.44	7,305	4.54	33,183
	MDF	0.0%	No data	No data	No data	No data
	HDF	0.1%	1.05	3	No data	No data
Lam Dong	MCF	97.6%	2.82	8,263	1.86	15,368
	MDF	1.3%	2.30	90	3.05	275
	HDF	1.1%	1.70	57	3.11	178
Total						73,926

This result in an estimate of just over 73,000 Mt CO₂e emitted per annum by the 14,100 farmers who participate in the various projects. Net emissions, or the carbon footprint, is considerably lower. When we include the three categories in Dak Lak and the monocrop and medium -diversified farms in Lam Dong for which we have sufficient data to estimate the footprint, emissions come in at 40,566 Mt CO₂e per annum. After factoring in carbon sequestration their footprint is 22,502 Mt CO₂e.

We then take the allocation of farmers in the entire sample across the diversification categories. We find that 66 percent of the farmers in our sample falls in the monocrop category, 7 percent is medium-diversified and 27 percent sits in the highly diversified category. We apply the number of farmers in each category and the average category farm size in our sample to determine which share of the sector level area belongs in which category. We estimate current total net emissions from coffee production in the Central Highlands by applying the same breakdown of farm types – and each category's average carbon footprints -- to the total production area in Central Highlands of 565,000 ha. (*Table 21*).

Table 21: Key metrics of net sector emissions calculation. Note that calculation factors are rounded, using these may give slightly different results from the ones displayed here.

a. Total area (ha)	Diversification	b. Share of sample (% area)	(a*b=c) Estimated sector area (ha)	d. Footprint (Mt CO ₂ e/ha)	(c*d) Contribution to sector net emissions (Mt CO ₂ e)
565,000	MCF	71%	400,216	1.56	622,622
	MDF	6%	35,470	1.49	52,790
	HDF	23%	129,415	0.99	128,107
Total					803,519

Our estimation of Vietnam's coffee sector greenhouse gas emissions at 803,519 Mt CO₂e per annum. Based on the aforementioned parameters, we model below what happens if additional farmers move into the highly diversified category from another farm type (*Figure 22*).

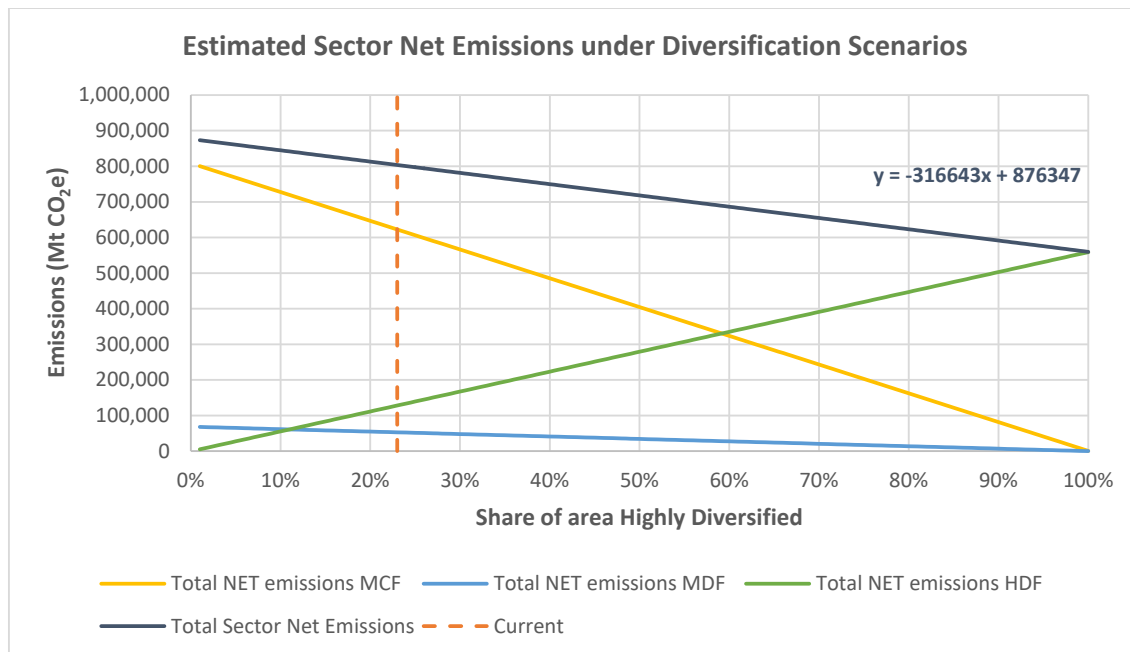


Figure 22: Estimated sector net emissions in Mt CO₂e under diversification scenarios and the contribution of each diversification category (MCF=Monocrop farms; MDF=Medium-diversified farms; HDF=Highly diversified farms) to total emissions.

The slope of the dark blue line indicates what we expect to happen to total net emissions from the Central Highlands coffee sector based on the percentage of farmers in the highly diversified category. This association comes in at 3,166 Mt CO₂e for each percentage point (Equation 1).

Equation 1: Linear equation describing how net sector level emissions develop as a function of the share of farmers in the highly diversified category. Where y=Net sector emissions in Mt CO₂e and x=Share of farmers in the highly diversified category

$$y = -316,643x + 876,347$$

We do not know how much it would cost to achieve a given reduction in net sector emissions through increasing diversification; if this were known it would be possible to estimate the cost per Mt CO₂e emissions avoided. Across the board, an increase of 10 percentage points in the share of highly diversified farmers is associated with a reduction in emissions of 2.8 percent. We allocate acreage to the highly diversified category in direct proportion to relative share of acreage under monocrop and medium-diversified farms. This would imply converting 56,610 ha of farms to the highly diversified category. Of this, 51,909 ha would come from monocrop farms and 4,601 ha would come from medium-diversified farms. Theoretically, if all farmers were to shift to the highly diversified category, the sector could decrease its net emissions from just over 800,000 Mt CO₂e to just under 560,000 Mt CO₂e. This is unlikely to happen – and may not be desirable given coffee yields on highly diversified farms tend to be a bit lower. On a relatively small number of farms this difference may not do much to total supply, but on a larger scale it could well drive a supply deficit.

How to replace the shortfall in supply? If history is any guide, then it is very likely that production shortfalls are compensated by new farmers entering the sector. A share of such new production is likely to come from newly cleared forests, be it in Vietnam or elsewhere. Diversification does not have to be a bad thing, on the contrary, but it can lead to unintended effects.

Another approach, probably with greater emissions reduction potential, is to adjust fertilizer use. The bulk of the emissions in production originates from fertilizers with nitrogen contributing most. In section 0 we found that nitrogen use per Mt GBE can be quite high, especially on less productive farms. We assume that the average optimal N use ratio is 120 kg/Mt GBE. While probably still on the high side, this is the average rate at which the farmers whose yields range from 2,500 to 3,500 kg GBE/ha use nitrogen. Current nitrogen use among all farmers in the sample amounts to 145 kg/Mt GBE. We modelled what would happen if emissions of farmers who apply nitrogen in excess of 120 kg/Mt GBE would move to this benchmark. We assume farmers using less than this value continue doing so. In this situation 0 percent of farmers apply nitrogen in excess of 120 kg N/Mt GBE and net sector emissions drop to 0.84 Mt CO₂e/ha. In combination with area data we can then estimate total net sector emissions (Table 22).

Table 22: Calculation factors to project effects of changes in share of farmers with nitrogen use in excess of 120 kg N/Mt GBE. Note that calculation factors are rounded, using these may give slightly different results from the ones displayed here.

a. Total area (ha)	b. Share of farmers with excess N application	c. Current net footprint (Mt CO₂e/ha)	d. Net footprint if 0% apply excess N (Mt CO₂e/ha)	(a*d=e) Net sector footprint if 0% apply excess N (Mt CO₂e)	((a*c)- e)/(b*100) Change in Mt CO₂e associated with 1 perc. point change in share
565,000	71%	1.42	0.84	475,558	4,685

Once we know the change in sector net emissions associated with a one percentage point change in the share of farmers using in excess of 120 kg N/Mt GBE, we can plot this as a function of total net sector emissions (Figure 23).

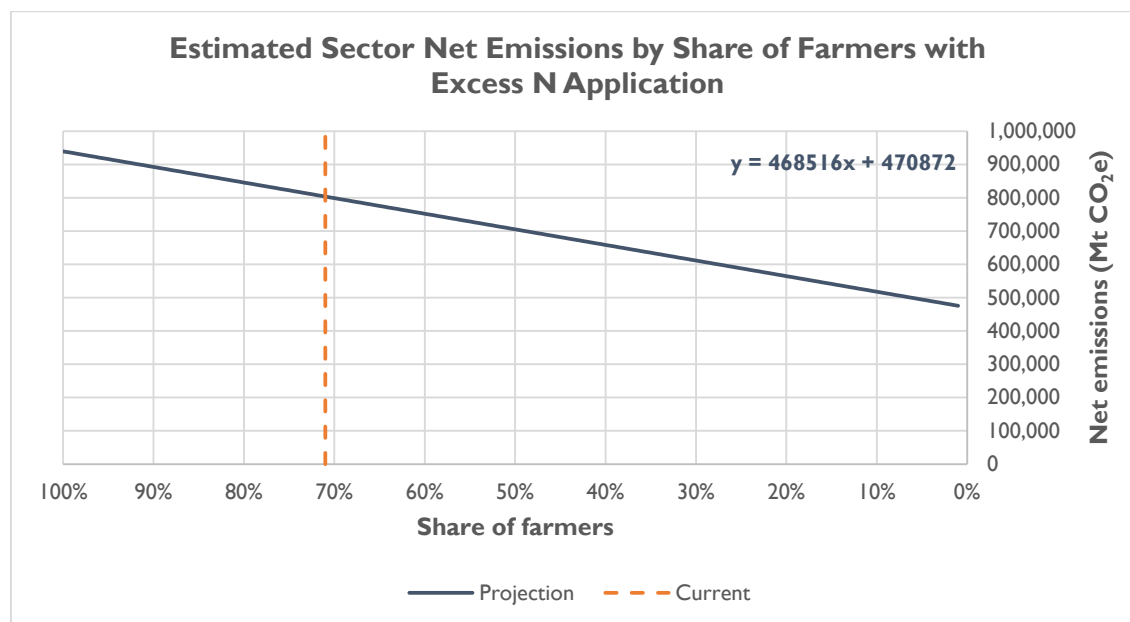


Figure 23: Scenario of the effect of different rates of farmers moving out of excess nitrogen use on net sector emissions in Mt CO₂e

The current situation, indicated by the orange dotted line in Figure 23, again intersects with the estimated net sector level emissions of just over 800,000 Mt CO₂e. The slope of the projected emissions is somewhat steeper at -4,685 Mt CO₂e with every additional percentage point of farmers moving to the assumed optimal nitrogen use of 120 kg/Mt GBE (Equation 2).

Equation 2: Linear equation describing how net sector level emissions develop as a function of the share of farmers who apply in excess of 120 kg N/Mt GBE. Where y=Net sector emissions in Mt CO₂e and x=Share of farmers with N application in excess of 120 kg N/Mt GBE

$$y = 468526x + 470872$$

By comparison, this implies that as an emission reduction strategy, optimizing fertilizer application is a lot more potent than promoting diversification. While the moving of an additional 10 percentage points of the coffee area into the highly diversified category would reduce sector net emissions by 2.8 percent, doing the same on nitrogen use would push down net emissions by 5.8 percent. The slope of the projected reductions if nitrogen use is optimized is more than 50 percent steeper than that of the diversification projection. Moreover, farmers who currently over-apply nitrogen would see a short-term reduction in cost of production which, if yields remain stable, translates into higher earnings. The focus of such efforts would have to be in Gia Lai province where 72 percent of the farmers in our dataset are above the 120 kg/Mt GBE mark, while in Dak Lak, Dak Nong and Lam Dong this is 30 percent, 24 percent and 36 percent, respectively. On the assumption that the Central Highlands have about 500,000 farmers (SCC, undated), this scenario would entail optimizing nutrient management on 50,000 farms.

4.4 Carbon footprint and farm profitability

In this section we investigate the relation between carbon footprint levels and profitability. We also look at which management practices influence profitability.

4.4.1 Relationship between footprint and profitability

Farms with positive footprints are significantly more profitable than those with negative footprints, but those with footprints in excess of 1.0 Mt CO₂e/ha are not more profitable than those in the range from 0 to 1.0 Mt CO₂e/ha, indicating that emissions in excess of 1.0 Mt CO₂e are not a prerequisite for profitable production.

When we compare profit between farms with positive and negative footprints (or net emissions), we count all revenue streams originating from the farm. For diversified farms, all revenues (and costs) of non-coffee products are factored in. In an outright comparison of farms with a positive and negative footprint, we find that farms with negative footprints are significantly less profitable (*Figure 24*). On average, the difference is about 20 million VND/ha (871 USD), which is fairly consistent over the seasons.

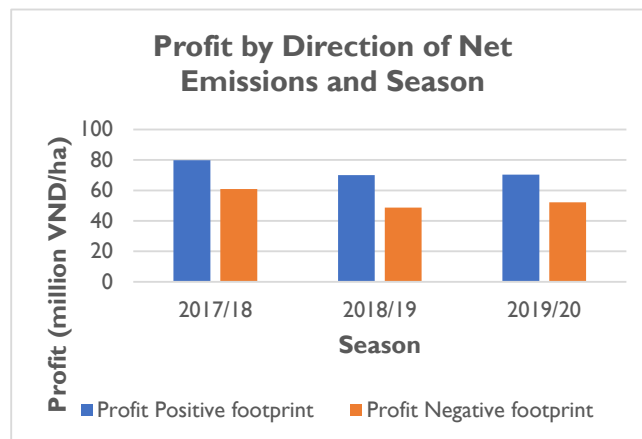


Figure 24: Profit in million VND/ha by direction of direction of net emissions and season

The binary distinction between farms by the direction of their footprint hides nuances in profitability levels in relation to the footprint. It might well be that farms with lower positive footprints are more profitable than those with high positive values. To analyze this further we break down the data in seven clusters of footprint levels (*Figure 25*).

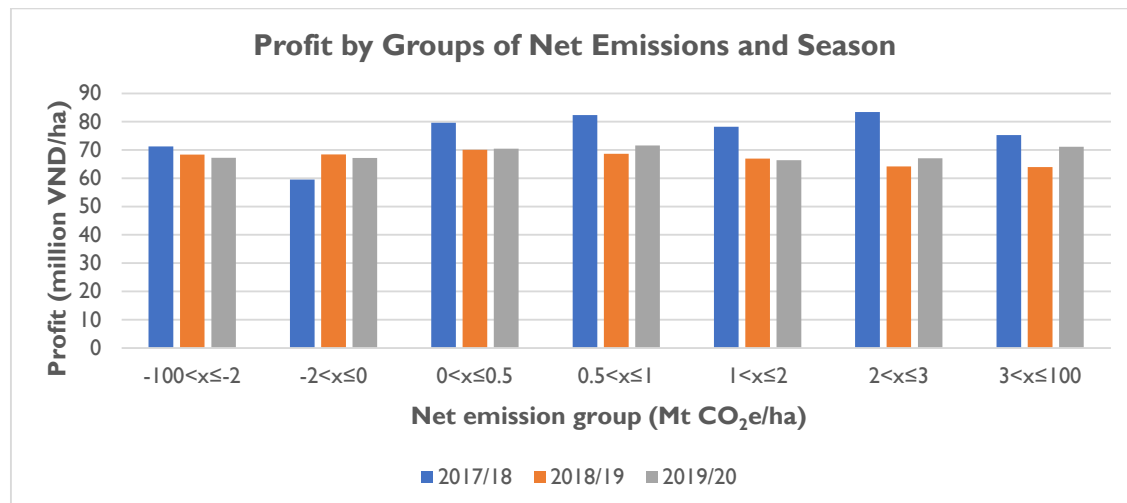


Figure 25: Profit in million VND/ha by groups of net emissions in Mt CO₂e/ha and season

Figure 25 shows that profit levels appear to be slightly higher in most seasons among farmers in the 0 to 0.5 and the 0.5 to 1.0 Mt CO₂e/ha groups. In comparison with farmers with higher emissions this difference is not

significant ($p=0.05$). To be profitable, net emissions need not be high. It is likely that profitability can be maintained and perhaps improved on farms with net emissions in excess of 1.0 Mt CO₂e/ha.

Part of the difference in lower profitability among farms with negative footprints is driven by lower coffee yields. Yields among this group of farmers are significantly lower ($p=0.05$) in each season compared to farmers with positive footprints. However, farmers in the 0 to 0.5 and 0.5 to 1.0 Mt CO₂e/ha groups have statistically similar ($p=0.05$) yields to those whose footprints exceed 1.0 Mt CO₂e/ha, while their fertilizer costs are significantly lower (Figure 26).

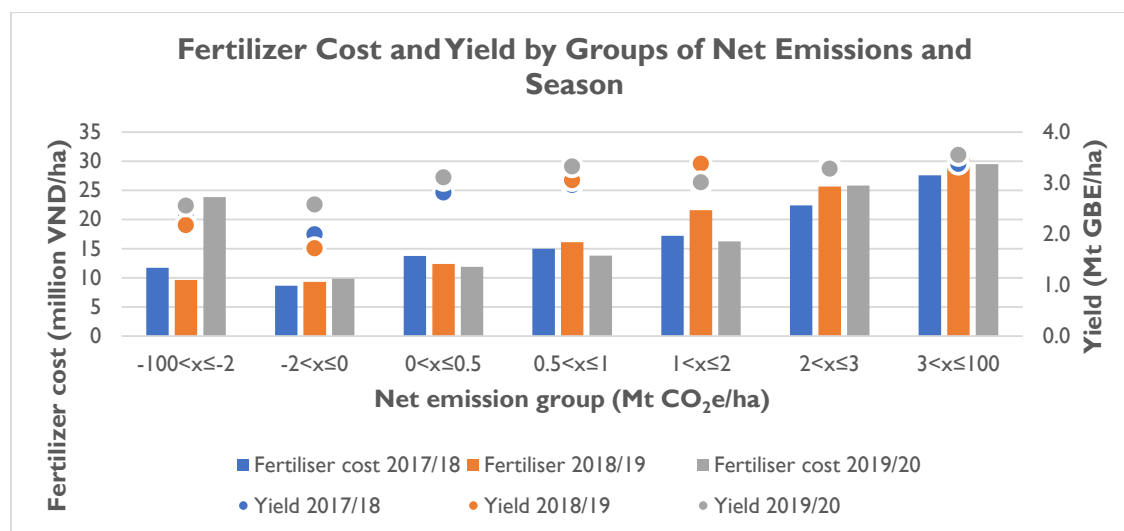


Figure 26: Fertilizer cost in million VND/ha and yield in Mt GBE/ha by groups of net emissions and season.

We find no meaningful correlation between fertilizer cost and yield. Judging by yield levels and fertilizer costs across the net emission groups, we think farmers who invest between 15 and 20 million VND/ha (650 USD-867 USD) in fertilizer are in the optimal range. This implies that farmers with net emissions in excess of 1.0 Mt CO₂e/ha have significant cost saving potential.

The greater yield volatility we observe on monocrop farms is also present in their profit levels. As with yields, in good years profits on monocrop farms tend to be higher, but their greater volatility may well introduce more financial uncertainty (Figure 27). In the definition we use, a monocrop farm can have up to 15 percent non-coffee trees, some of which may also generate revenue streams. Although monocrop farms derive a far greater share of their revenues from coffee (97 percent) compared to medium and highly diversified farms, coffee is not their only source of revenue (Figure 28). Highly diversified farms obtain more of their revenues from non-coffee crops; their long-run average contribution of non-coffee revenue comes in at 31 percent.

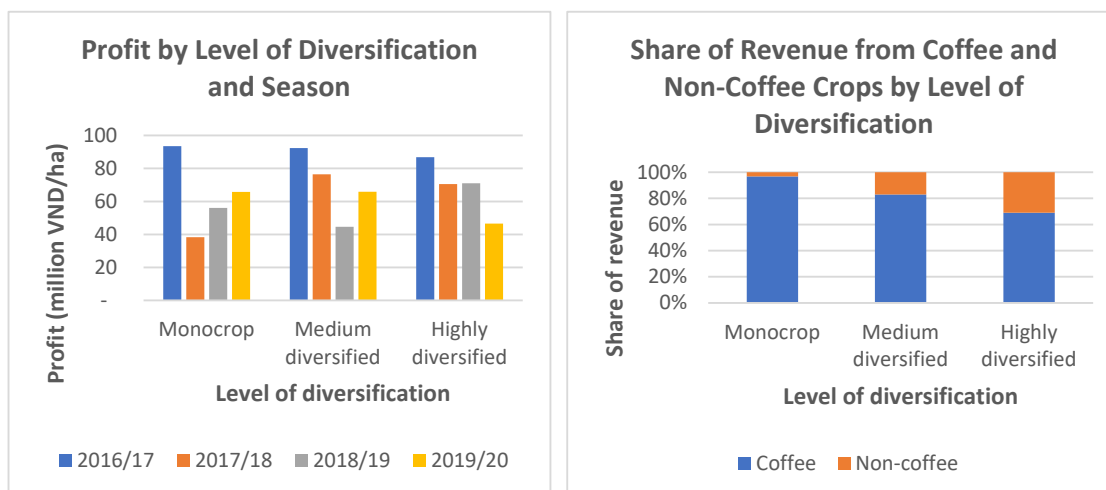


Figure 27: Profit in million VND/ha by level of diversification and season

Figure 28: Long-run average contribution to revenue from coffee and non-coffee sources by level of diversification

One of the sub-research questions related to the application of organic management, and whether organically managed farms are more carbon efficient. In our sample we had no farmers who relied exclusively on organic inputs to provide nutrients to the coffee, so this analysis cannot be conducted. Trinh et al (2018) did conduct this analysis in Vietnam and found a result of 0.64 Mt CO₂e/Mt GBE in organic Robusta production, some 32 percent lower than conventional farms in their sample. However, they neglected to outline the yield, cost, and profitability levels of the two systems, so we cannot judge if the organic production system makes sense for farmers currently nearly exclusively using conventional approaches. In light of the yield differential between say Vietnam with conventional production and Uganda with more organic Robusta production, and the fact that so little organic production takes place in Vietnam despite organic coffee being a mainstream product for a number of years, we think farmers have already decided that organic coffee production does not work for them. This aligns with findings of Vossen (2005) who concluded that organic coffee production is not serving the interest of producers. Among other challenges to sustain viable yield levels, which he sets at 1.0 Mt GBE/ha, farmers need such large volumes of compost and manure organic production is unviable for most. Compare that with long-run average yield levels of 2.84 Mt GBE/ha helps explain why the uptake of organic coffee production in Vietnam is extremely low.

4.4.2 Differences in profitability trends across geographies

In Dak Lak farms with positive footprints are significantly more profitable than those with negative footprints. In both Dak Lak and Lam Dong farmers with footprints in excess of 1.0 Mt CO₂e/ha are not more profitable than those who sit in the range from 0 to 1.0 Mt CO₂e/ha indicating that emissions in excess of 1.0 Mt CO₂e are not a prerequisite for profitable production. Ethnic minority farmers tend to lag in yields in Lam Dong province. We think it is likely that this may also be the case among certain ethnic groups in other provinces, but lack data to confirm.

The trends we observed across the entire population apply to the provinces for which we can calculate the footprint (Figure 29), but the provincial breakdown does have some limitations. The group of negative footprint farmers in Lam Dong numbers no more than 13 in any of the three seasons and is exceedingly small.

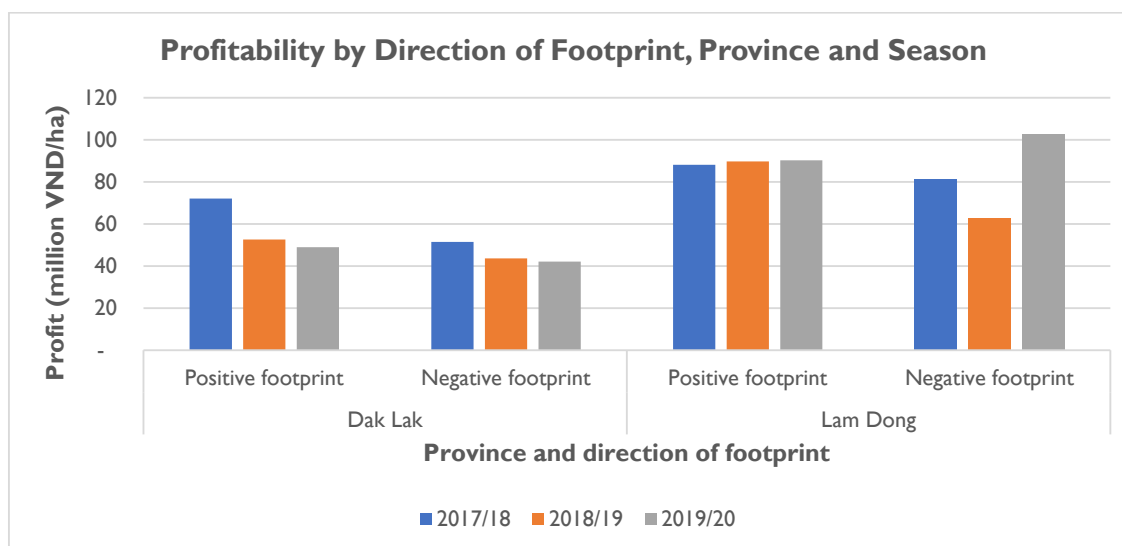


Figure 29: Profitability in million VND/ha by direction of carbon footprint, province, and season. Note that the sample size in Lam Dong for the negative footprint group is 13, 6 and 8 in the respective seasons and hence not reliable.

In Dak Lak, where sample sizes are sufficient, we find a similar trend to what we observed at population level, albeit with smaller differences in profitability between the groups. In the 2017/18 season the difference amounted to just over 20 million VND/ha (867 USD), but this narrowed to 8.9 and 6.8 million VND/ha (387 USD and 296 USD) in subsequent seasons.

Also here, a breakdown of the footprint values in a range of seven different levels provides more detailed insights (Figure 30).

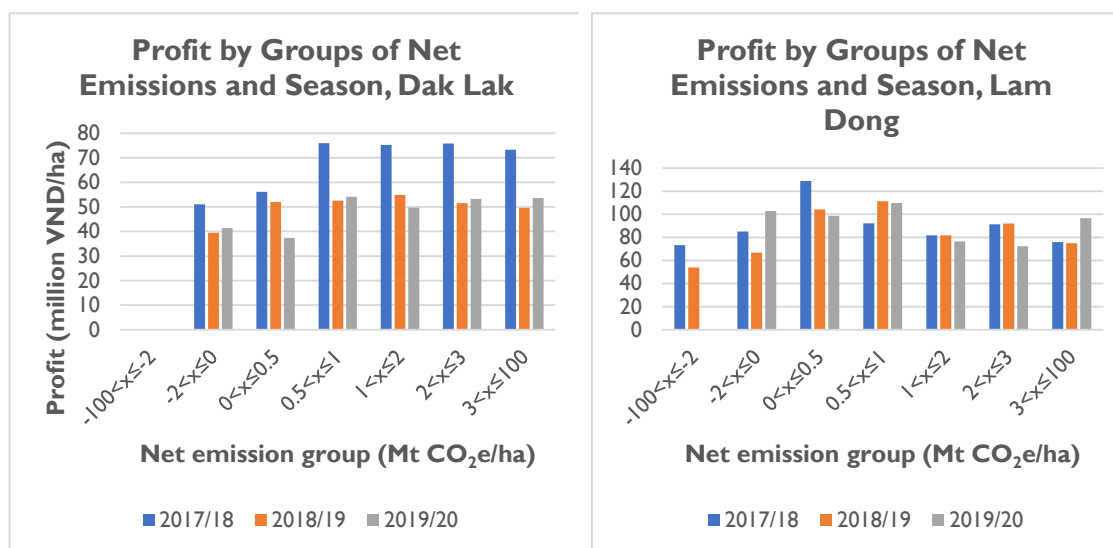


Figure 30: Profits in million VND/ha by net emissions groups in Mt CO₂e/ha, province, and season

The pattern in Dak Lak shows no significantly higher profits in groups with greater net emissions. In Lam Dong the situation is more distinct. There is a clear optimal emission range. Farmers in the 0 to 0.5 and 0.5 to 1.0 Mt CO₂e/ha groups have significantly higher profits in all but one season and group combination than those with footprints in excess of 1.0 Mt CO₂e/ha (Table 23).

Table 23: Average fertilizer cost in VND/ha, yield in Mt GBE/ha and profit in VND/ha for the 2019/20 season by province and net emission group in Mt CO₂e/ha. Post-hoc comparison of differences between net emission group within province using Tukey's HSD test. Mean values are shown, letters indicate significant differences at the p=0.05 level

Province	Net emission group (Mt CO ₂ e/ha)	Fertilizer cost (VND/ha)	Yield (Mt GBE/ha)	Profit (VND/ha)
Dak Lak	-100<x≤-2	No data	No data	No data
	-2<x≤-0	10,784,751	2,366	41,396,603 ^a
	0<x≤0.5	12,033,644	2,369	37,361,906 ^a
	0.5<x≤1	13,405,139	2,336	54,093,967
	1<x≤2	14,910,771	2,414	49,730,148
	2<x≤3	23,179,212 ^a	2,833 ^a	53,243,523
	3<x≤100	28,372,039 ^a	2,855 ^a	53,604,998
Lam Dong	-100<x≤-2	No data	No data	No data
	-2<x≤-0	5,331,771 ^a	2,782 ^a	102,748,857
	0<x≤0.5	11,680,222	3,575	98,571,248
	0.5<x≤1	14,207,440	3,701	109,787,855
	1<x≤2	17,112,849	3,791	76,463,275 ^a
	2<x≤3	28,149,288 ^b	3,898	72,371,236 ^a
	3<x≤100	31,178,569 ^b	3,747	96,703,987

For simplicity, we only show the 2019/20 outcomes in [Table 23](#), but a similar trend is observed in previous seasons. While coffee yield levels tend to be higher among the top net emission groups, profitability does not follow the same pattern. In Dak Lak we find no significant difference in profit among the top four groups while in Lam Dong profits were lowest among the groups with net emissions ranging from 1 to 3 Mt CO₂e/ha.

Vietnam has a large number of ethnic minority groups, some of which show markedly different performance in terms of yields and profitability, while others are on par with the Kinh majority group. We do not have ethnic background data for all farmers in the sample, but in most years, we know for the majority of farmers whether they belong to the Kinh majority group or any of the minority groups. This information is available for 46 percent of the sample; among them 75 percent belong to the Kinh majority group. Given that performance between the groups may differ, it may make sense to provide different types or frequency of services to different groups. To determine this, we compare emission and yield profiles among ethnic groups ([Figure 31](#)).

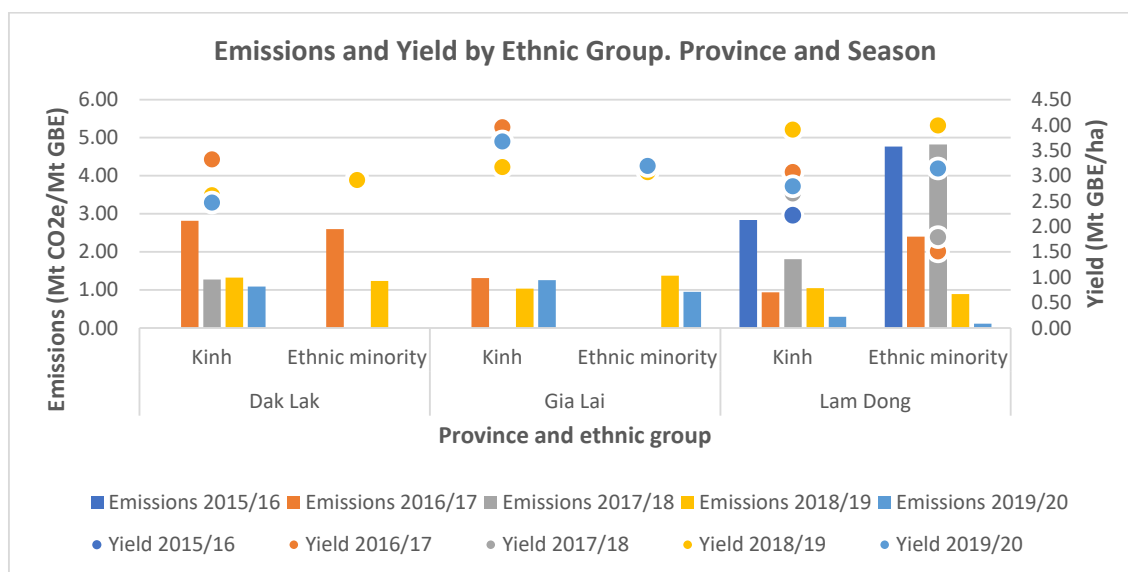


Figure 31: Emissions in Mt CO₂e/Mt GBE and yield in Mt GBE/ha by ethnic group, province, and season.

At first glance [Figure 31](#) shows a difference in performance between the groups in 2015/16, 2016/17 and 2018/19 seasons in Lam Dong. In the other provinces differences also occur but appear less pronounced. Subsequent testing shows minority farmers in Lam Dong tend to have higher emissions per Mt GBE and lower yields and higher emissions ([Table 24](#)).

Table 24: Average emissions in Mt CO₂e/Mt GBE and yield in Mt GBE/ha by ethnic group, province, and season. Post-hoc comparison of differences between ethnic groups on emissions and yield within each province and season combination using Tukey's HSD test. Mean values are shown, asterisks indicate significant differences at the $p=0.05$ level

			Season				
			2015/16	2016/17	2017/18	2018/19	2019/20
Emissions (Mt CO ₂ e/Mt GBE)	Dak Lak	Kinh	No data	2.82	1.27	1.32	1.09
		Minority	No data	2.60	No data	1.24	No data
	Gia Lai	Kinh	No data	1.31	No data	1.04	1.26
		Minority	No data	No data	No data	1.37	0.95
	Lam Dong	Kinh	2.84	0.94	1.81	1.05	0.30
		Minority	4.77*	2.40*	4.82*	0.89	0.11
Yield (Mt GBE/ha)	Dak Lak	Kinh	No data	3.32	2.55	2.62	2.47
		Minority	No data	2.97	No data	2.91	No data
	Gia Lai	Kinh	No data	3.95	No data	3.17	3.67
		Minority	No data	No data	No data	3.07	3.19
	Lam Dong	Kinh	2.22*	3.07*	2.65*	3.91	2.79
		Minority	1.59	1.51	1.79	3.99	3.14*

In the other provinces, differences in emissions or yield are not significant between the ethnic groups in any of the seasons for which we have data. Some ethnic minority groups are on par with Kinh farmers, whereas

others have a greater tendency to lag in yield. In the absence of more detailed information on ethnic background beyond belonging to the Kinh group or not, we cannot target more intensive support to any one group. Based on our experience, it is highly likely there are groups in need of more support, but available provincial data does not show any statistically significant differences.

4.5 Effectiveness of interventions

In this section we map the trends in fertilizer use and diversification and we attempt to untangle the relation between the support farmers have received from the partners and farm level changes observed.

4.5.1 Trends in fertilizer use

Fertilizer use as measured by nitrogen applications per ha has been trending down in Dak Lak and Lam Dong, but not in Gia Lai. Despite regional decreases in Gia Lai, all districts in 2019/20 remain above the 120 kg N/ Mt GBE benchmark. Districts in the north-east of Lam Dong remain above the benchmark despite significant improvements.

After hired labor, fertilizer expenditures tend to be the second most costly investment farmers make during a production season (IDH, 2019). From a carbon footprint perspective, fertilizer is the single most important contributor to GHG emissions as we could see from the preceding analysis. Trends in fertilizer use therefore matter. We can plot fertilizer cost changes over time (Figure 32). However, costs may increase even as actual nutrient usage goes down as a result of inflation or because farmers change fertilizer types. It is useful to look at volumes of single element nutrients. We focus on nitrogen use given its outsized contribution to fertilizer-related emissions (Figure 33).

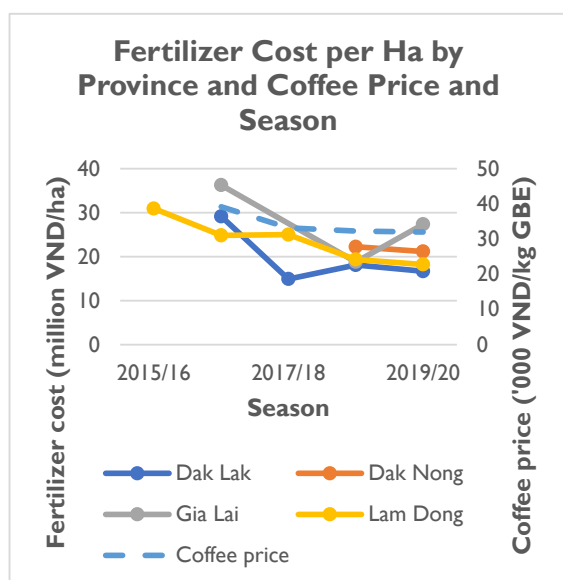


Figure 32: Fertilizer cost in million VND/ha by province and season

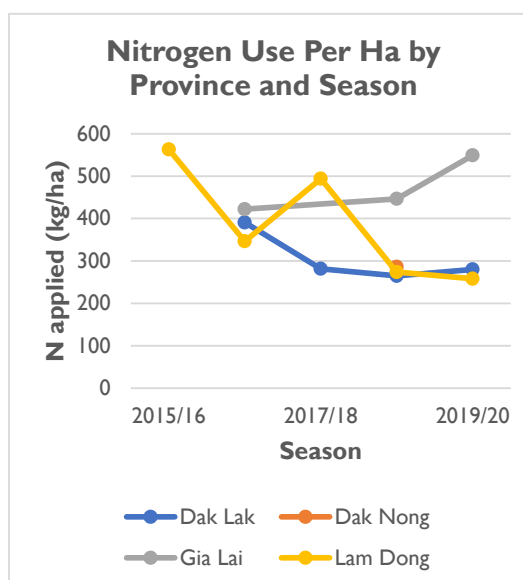


Figure 33: Nitrogen use in kg/ha by province and season. Note that in 2019/20 season in Dak Nong only fertilizer costs were available, not the types and volumes used

Across the population in our sample we see a reduction in nitrogen use in two of the four provinces. Only in Gia Lai do we see an increase, while in Dak Nong we only have one year's worth of data. The fertilizer cost and nitrogen application lines follow roughly the same pattern with an increase in Gia Lai and a general downward trend in Dak Lak and Lam Dong.

Averages across the provinces hide some major changes within districts. And while per ha figures are useful, it is also relevant to understand how much coffee is produced with every unit of nitrogen applied. In line with the projection in section 0, we plot the nitrogen use in kg/Mt GBE by district such that we can see which districts are under, close to, or over the 120 kg N Mt GBE benchmark. To maximize the available data, which is not complete for every district in every season, we take the average N use over the first four seasons and then plot the change from that to the most recent value in 2019/20. This maximizes the number of observations we can show (Figure 34).

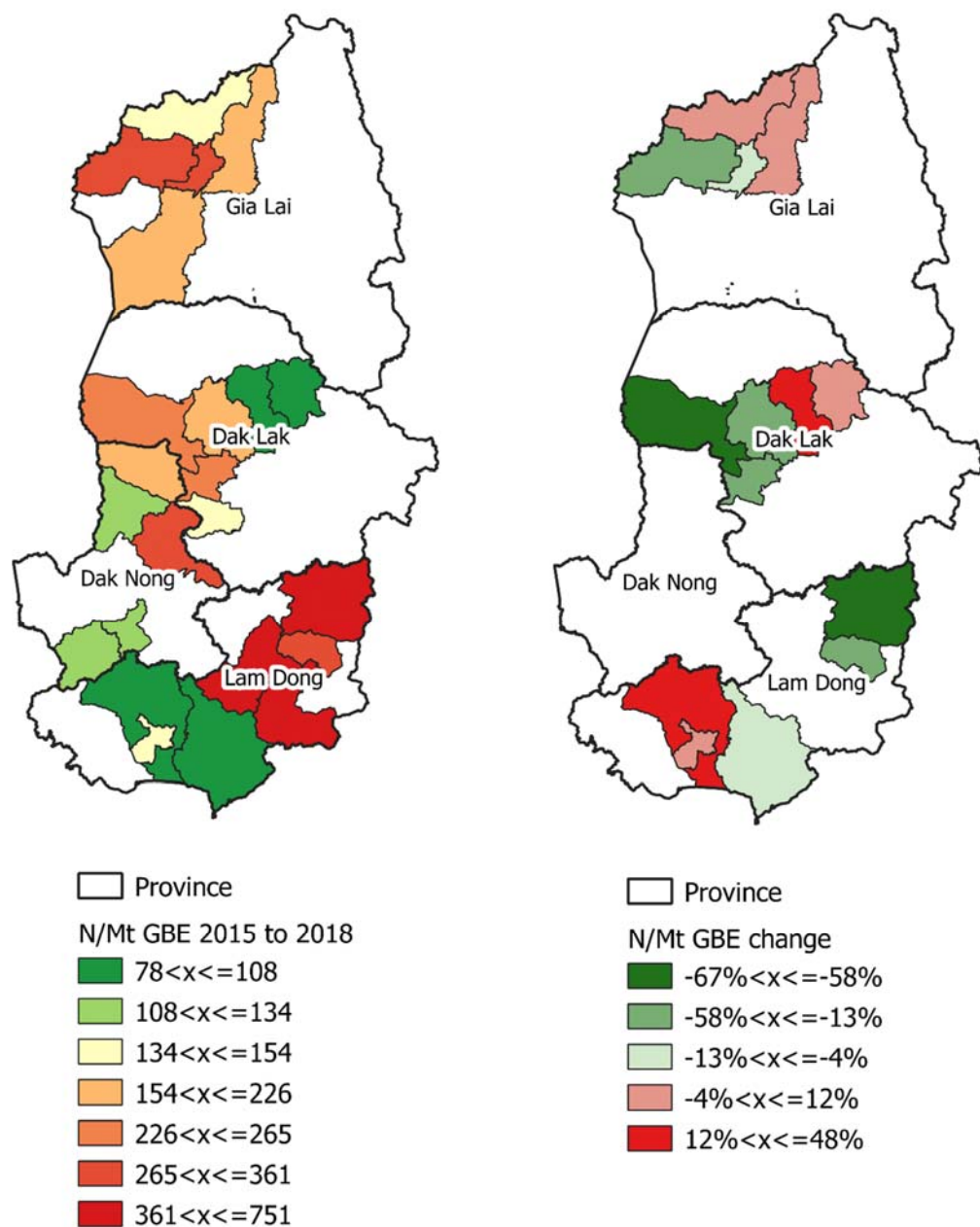


Figure 34: District level average seasonal nitrogen use in kg/Mt GBE from 2015/16 to 2018/19 and change from that period to 2019/20

We observe a number of districts in north-east Lam Dong, eastern and southern Dak Lak and Gia Lai where average nitrogen use per Mt GBE exceeds the assumed optimum of 120 kg/Mt GBE. South central Lam Dong, and, in particular, the largest production area of Di Linh district is below that level, while three out of four districts in Dak Nong are either just below or very close to it. Main challenges are in the Arabica-growing area of north-west Lam Dong, eastern Dak Lak and Gia Lai province where, on average, farmers continue to apply above the benchmark of 120 kg N/Mt GBE. In some of those areas, we do see positive developments. The right-hand map in [Figure 34](#) shows the relative change in nitrogen use per Mt GBE. It plots the relative change from the average of the 2015/16 to 2017/18 period and compares it with the most recent figures for the 2019/20 season. Of the 14 districts we can assess, we find two to three districts in each province where reductions have taken place. While Bao Lam district in Lam Dong shows a significant increase, but in 2019/20 it is still just below the 120 kg/Mt GBE mark. The areas deserving prioritized attention are those where nitrogen use was already in excess of the benchmark and then showed an increase over time. Examples include Dak Doa and Chu Pah districts in Gia Lai and Da Lat and Lac Duong in Lam Dong.

4.5.2 Trends in diversification

The share of farmers across the levels of diversification appears to be quite stable across the seasons in each province. Major shifts are driven by sample changes rather than major on -the-ground developments. Most non-coffee tree planting efforts are from 2011 to 2015, when it tails off. Regionally, districts in Dak Lak and Dak Nong see most planting efforts.

In light of the projects' general goals, promotion of diversification is on the agenda. We find that shifts of farmers from the monocrop to medium-diversified and highly diversified categories is not really changing significantly over time ([Figure 35](#)).

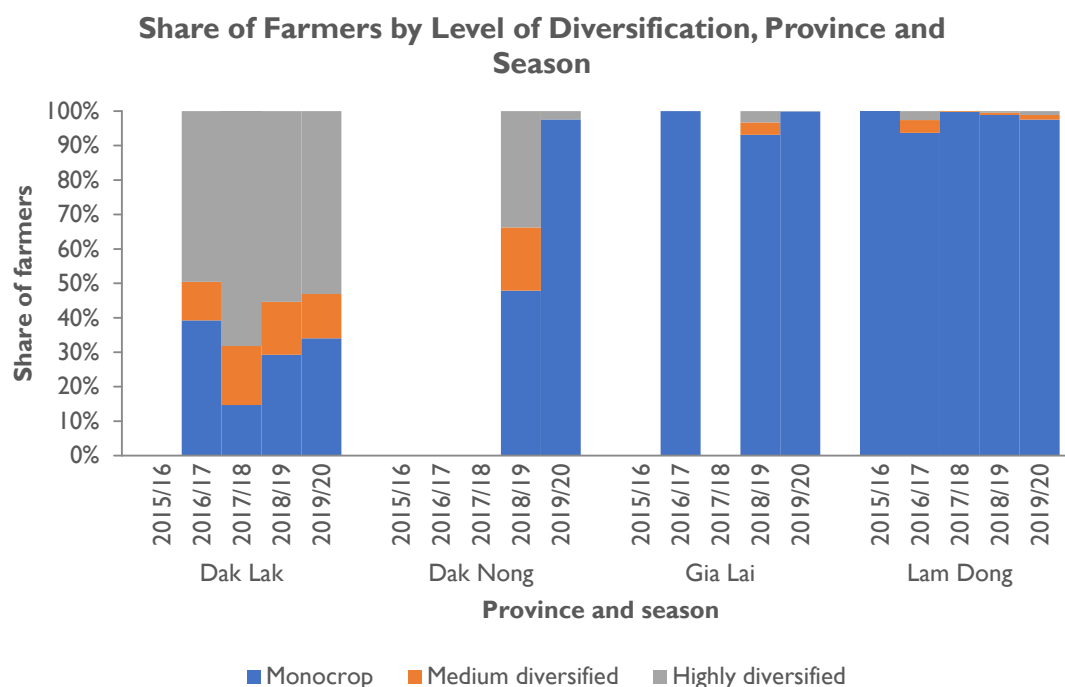


Figure 35: Share of farmers by level of diversification, province, and season.

In Dak Lak and Dak Nong, much of the shift from one category to the next is driven by changes in the sample. We observe a slight movement in Lam Dong province where the sample went from 100 percent monocrop

production in 2015/16 to a few percentage points of more diversified farms in subsequent seasons, but the categorization boundaries may hide planting activities of monocrop farmers who planted trees but remain below the 15 percent threshold for inclusion in the medium-diversified category. To ascertain if that is the case, we also plot the cumulative number of non-coffee trees planted per farm over the past ten years (*Figure 36*).

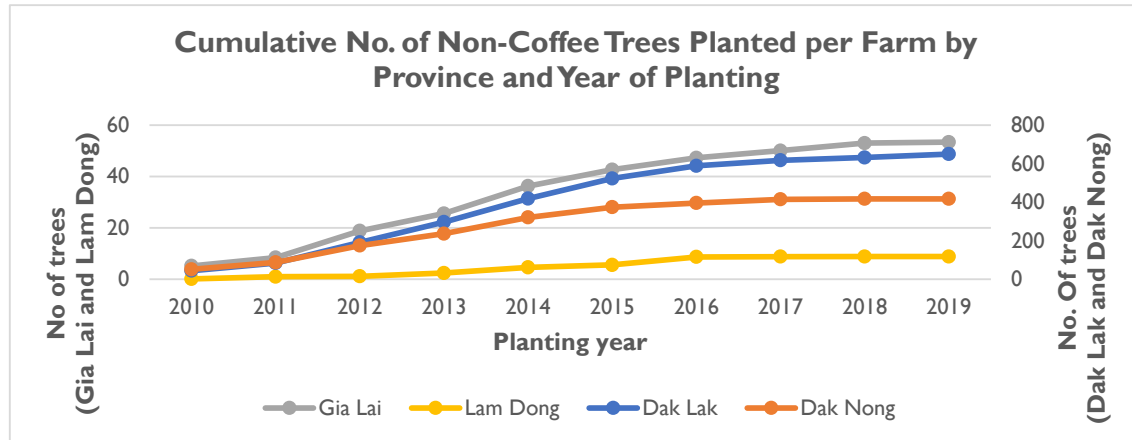
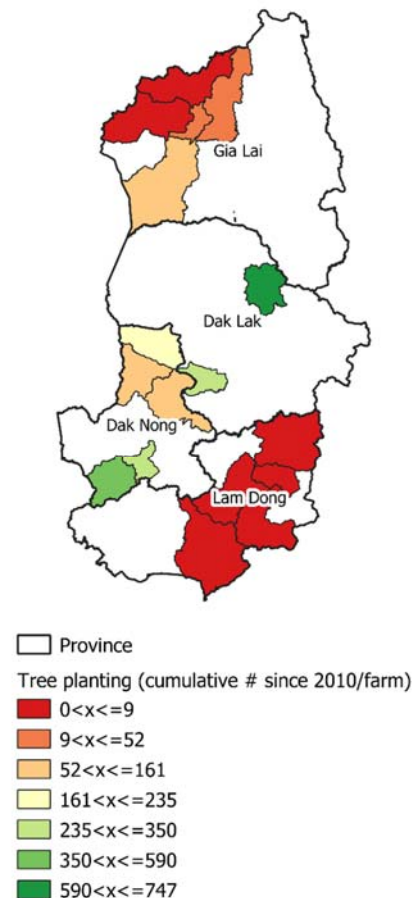


Figure 36: Cumulative number of non-coffee trees planted per farm by year of planting and province, stocks inventoried in the 2018/19 season.

The steepest section of the curve in *Figure 36* falls roughly in the period 2011 to 2015, while projects that supplied data started no earlier than 2016. Planting rates start to tail off from 2016 onwards. For Dak Lak and Dak Nong this is understandable; farms simply run out of space to plant more trees. In Gia Lai and Lam Dong this point has not yet been reached. It would be important to better understand how diversification efforts have been conducted in these provinces and what challenges project teams and farmers face.

Regionally, planting of non-coffee trees lags in Lam Dong province and Gia Lai (*Figure 37*). We find the highest planting rates in Dak Lak and Dak Nong but note that not all districts in the dataset have sufficient information on the number and years in which trees were added to the farm to analyze.

Figure 37: Cumulative number of non-coffee trees planted per farm from 2010 to 2019 by district.



5.1.3 Effect of interventions by partners on diversification and fertilizer use

Data on service delivery by partners to farmers is only available for a small part of the population during the past two seasons. We are very limited in what we can analyze on how interventions are affecting farmers' performance and behavior. We see significantly lower nitrogen use among farmers in Dak Nong province who received soil tests, but data covers a single season so we cannot control for pre-test nutrient management on those same farms. Overall, if partners want to know how interventions are affecting farmers' behavior, complete service delivery data should be collected.

Data on project partners' interventions is patchy. We enquired about the delivery of a range of services from training on Good Agricultural Practices to soil testing, fertilizer advice and seedling distribution. One of the partners had no such data available, for another partner all farmers were indicated to have received the exact same amount of training on Good Agricultural Practices (GAP). Two partners had more information available, but for one of them the matching of service records to farmers' data resulted in just 5 percent of the farmers in the data set being successfully matched, while for another partner, coverage is incomplete. Lack of data hampers a meaningful analysis of the relationship between interventions and changes in emissions. Among the farmers for whom we do have service data, nearly all of it concerns training on Good Agricultural Practices and then only for the two most recent seasons (**Error! Reference source not found.**).

Further compounding the lack of available data is the lack of variability. Of the farmers who received GAP training, 81 percent received 3 training sessions. In the absence of variability in access to service, it is not possible to correlate this with changes in fertilizer use or diversification.

Aside from GAP training, 224 farmers in the sample received fertilizer advice in 2018/19 and another 89 received soil testing services.

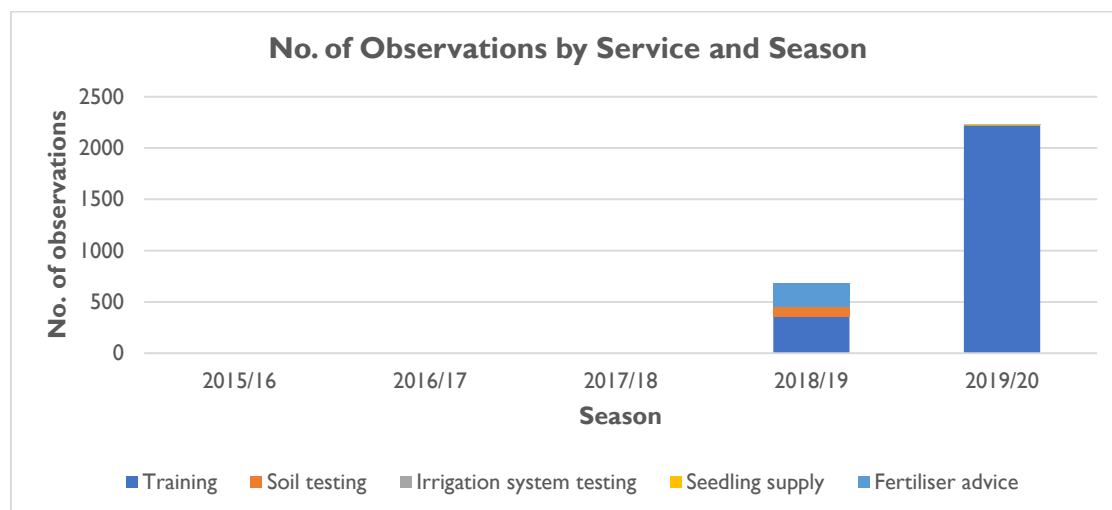


Figure 38: Number of observations by type of service delivered to farmers and season.

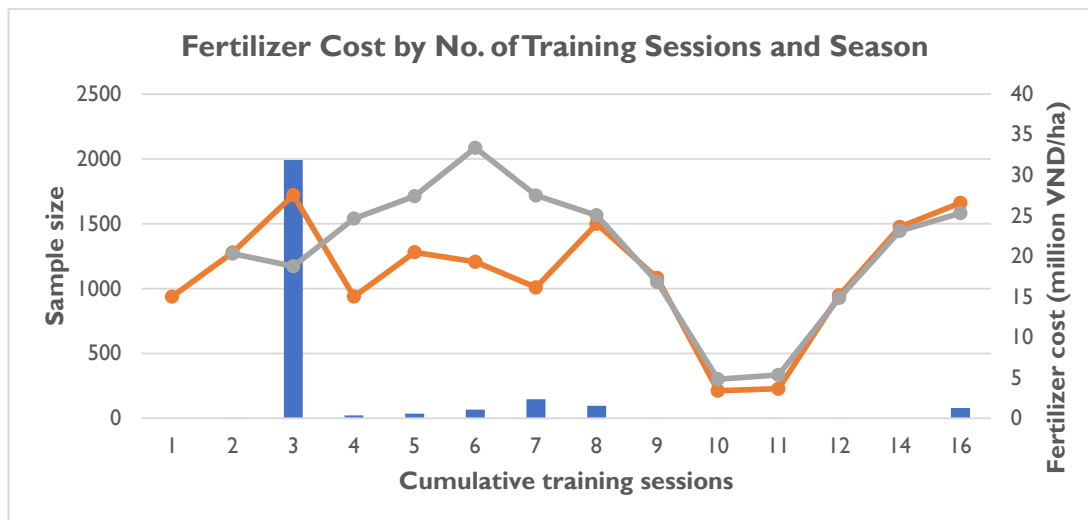


Figure 39: Fertilizer cost by cumulative number of training sessions on Good Agricultural Practices and season and sample size of cumulative training sessions

We did attempt to analyze the relation between GAP training and fertilizer use, but skewed observations make it hard to draw conclusions. Fertilizer costs between seasons of farmers who have received more than seven training sessions show less variability from one season to the next (Figure 39). However, the differences we see with farmers who have received up to seven sessions are not significant ($p=0.05$).

We do have some data on fertilizer extension services/ advice. Farmers who received this service are located in Gia Lai and Dak Nong provinces.; we only have one year of data and cannot ascertain if and how such advice affects nutrient management in subsequent years. We do find slightly lower nitrogen applications among farmers who received fertilizer advice in Gia Lai, 451 kg/ha versus 471 kg/ha, but this difference is not significant ($p=0.05$). The difference between the two groups in Dak Nong is less than 1 kg/ha. In our experience however, it usually takes at least two seasons before farmers start making wholesale changes to their management, if at all. Therefore, multiple years of consistent data on performance and services are required to better understand the effects that services may have on farmers' behavior and decision-making.

The soil testing data is available for the same provinces, but covers just five farmers in Gia Lai, a number too small to be used in meaningful analysis. In Dak Nong we find a significant difference ($p=0.05$) in nitrogen use per ha with a rate 335 kg/ha being applied by farmers who received soil tests versus 480 kg/ha among those who did not. As we only have a single year of data, we cannot exclude that the farmers with soil tests already had lower nitrogen use levels before they received the tests, so we cannot conclude that soil testing resulted in closer to optimal nitrogen usage, but the difference we appear promising.

Analysis of service delivery in relation to diversification is even more fraught. There is very little overlap between farmers for whom we have tree stock data over time and for whom we have training data. Consequently, we are not able to see how one is affecting the other. There are a few data points on seedling supply. Many of the partners have worked on this topic, but we only have data on six farmers' use of such service for the 2019/20 season.

5. Conclusions

5.1 Carbon emissions

Carbon emissions were 3.21 Mt CO₂e/Mt GBE in 2015/16 and have decreased significantly to 1.22 Mt CO₂e/Mt GBE in 2019/20. Fertilizer contributes more than 83 percent to emissions, with nitrogen being the single largest contributor. In the driest season, the contribution of energy use for irrigation is significantly higher than in seasons with more favorable rainfall.

CO₂e emissions per unit coffee vary significantly across groups of farmers with different yield levels. Farmers with yields of less than 1,250 kg/ha have a five-year average emission of 2.50 Mt CO₂e /Mt GBE versus 1.01 Mt CO₂e/Mt GBE among farmers with yields in excess of 3,500 kg/ha. This is driven largely by over-application of nitrogen by less productive farmers. Monocrop farmers emit significantly higher volumes of GHGs per unit coffee than medium and highly diversified farmer and in the two most recent seasons, also on a total emissions per ha basis.

Coffee yields over time are much more volatile on monocrop farms, yet their long-run average yield is significantly higher than that of medium-diversified farms, which in turn are higher than those on highly diversified farms. There seems to be a trade-off for monocrop systems. They appear to be more vulnerable to adverse or changing weather conditions, and from a resilience perspective promoting diversification may be advisable. Emissions have reduced significantly from 2016/17 to 2018/19 and 2019/20, irrespective of the level of diversification. This may be driven by declining coffee prices over the same time frame resulting in lower fertilizer applications.

The three provinces for which we have data on emissions over time show diverging patterns. Emissions in Dak Lak have reduced significantly from 2016/17 to 2018/19 from 1.74 Mt CO₂e/Mt GBE to 0.86 Mt CO₂e/Mt GBE. In Lam Dong, emissions show a similar trend, moving from 1.26 Mt CO₂e/Mt GBE to 0.92 Mt CO₂e/Mt GBE in the same time frame. Gia Lai, where more than 70 percent of farmers overapply fertilizer, has a significant increase from 1.59 to 1.85 CO₂e/Mt GBE. At district level, increases in emissions are predominantly found in Lam Dong province.

5.2 Carbon stocks

Monocrop farms, which tend to be older, had carbon stocks of 41.6 Mt CO₂e/ha in 2016/17, significantly more than highly diversified farms whose tree stocks are larger but more recently planted. As coffee is being replaced, the sample stabilizes and tree stocks on more diversified farms are maturing, the carbon stocks on medium and highly diversified farms (>42 Mt CO₂e/ha) outstrip that of monocrop farms (34.0 Mt CO₂e/ha) in 2019/20 by a significant margin.

Carbon stocks tend to be stable on more mature farms, but we find a strong dip in stocks in the 2018/19 season from around the 40 Mt CO₂e/ha mark to around 32 Mt CO₂e/ha. This is driven by inflow of new farmers into the sample and replanting activities. We find no significant difference in carbon stocks between levels of diversification, although we expect that to materialize over time as much planting is recent. Stock levels in 2019/20 have recovered to statistically higher levels in Dak Lak compared to 2016/17 and appear to be on track to do so next season in Lam Dong.

5.3 Carbon footprint

The carbon footprint on a per ha basis on highly diversified farms is significantly lower than on monocrop farms. In part this is because of higher carbon sequestration rates, but more importantly by lower emissions. Across the three levels of diversification, we observe a downward trend over time in carbon footprints per ha.

Nearly one-third of the highly diversified farms had a negative carbon footprint in the 2019/20 season. While this share was lower in previous seasons, it is significantly higher when compared to monocrop and medium-diversified farms in each of the seasons. Irrespective of the level of diversification, negative footprint farms spend significantly less on fertilizer, but their yields are also lower.

By province, the share of farms with negative carbon footprints is highest in Dak Lak at 32% of the highly diversified farms. In Lam Dong, such farms are rare and consequently the share of farmers with negative footprints is lower at 14% and 16% respectively for monocrop and medium-diversified farms. Data for this analysis is drawn from a limited number of districts and is not representative for the wider sector.

In the coffee sector, most carbon footprint work has focused on Latin America and on Arabica production. Very few benchmarks are available for Robusta coffee. The few studies that focus on Robusta footprints in Vietnam find comparable values to our work, albeit from a far smaller sample.

Across the various projects of the partners we estimate that the 14,100 farmers they engage with emit close to 74,000 Mt CO₂e per annum. At sector level in the Central Highlands we estimate total net emissions to be just over 800,000 Mt CO₂e per year. Reducing this can be achieved by increasing diversification, but a more impactful approach would be to optimize fertilizer use and nitrogen use in particular.

5.4 Carbon footprint and profitability

Farms with positive footprints are significantly more profitable than those with negative footprints. But in both Dak Lak and Lam Dong provinces, farmers with footprints in excess of 1.0 Mt CO₂e/ha are not more profitable than those who sit in the range from 0 to 1.0 Mt CO₂e/ha indicating that emissions in excess of 1.0 Mt CO₂e are not a prerequisite for profitable production.

Ethnic minority farmers tend to lag in yields in Lam Dong province. This is likely the case for certain ethnic groups in other provinces, but do not have sufficient data to confirm.

Fertilizer use, as measured by nitrogen applications per ha, has been trending down in Dak Lak and Lam Dong, but not in Gia Lai. Despite regional decreases in Gia Lai, all districts in 2019/20 remain above the 120 kg N/ Mt GBE benchmark. Also districts in the north-east of Lam Dong remain above the benchmark despite significant improvements.

The share of farmers across the levels of diversification appears to be quite stable across the seasons in each province. Major shifts we see are driven by sample changes rather than major on-the-ground developments. Most non-coffee tree planting efforts, concentrated in Dak Lak and Dak Nong, are from 2011 to 2015, after which it tails off.

5.5 Effectiveness of interventions

Data on service delivery by partners to farmers is only available for a small part of the population during the past two seasons. This limits any analysis of if and how interventions affect farmers' performance and behavior. We see significantly lower nitrogen use among farmers in Dak Nong province who received soil tests, but data covers a single season so we cannot control for pre-test nutrient management on those same farms. Overall, if partners want to learn if and how interventions are affecting farmers behavior, they should collect complete, consistent and ideally standardized service delivery data.

6. Recommendations

Recommendations are divided in four sections: i) Data; ii) Interventions; sub-divided into: ii.a) Optimizing nutrient management and ii.b) Diversification; and iii) Considerations for further research.

6.1 Data

While we have been able to conduct a large number of analyses, some topics remain unclear. A severe limitation was the discontinuity of much of the available data. At least within partners' projects, we strongly recommend ensuring regular surveys conducted once per season among the same set of ideally randomly-selected farmers to build up a balanced panel data set. Such efforts should be integrated in the various projects from the start so changes can be observed over the project's lifetime.

If applying random sampling, we should also avoid the phenomenon observed in some of the data sets where most farmers interviewed were located closely to the main roads and less so in the interior of a district or commune.

When multiple implementers are working with the same roaster and institutional partners, as in this case, it makes sense to try and align and standardize information collected. We recommend all partners use the Global Coffee Platform (GCP) data collection tool where feasible. Data from GCP was the most complete for this type of analysis. With additional programming, variables collected with the GCP tool can also be used to provide carbon footprint reports among other analyses.

For project and program funders such as JDE and IDH, it is recommended to ensure that: i) projects have an adequate geographical coverage, such that at least all the top-five producing districts in each of the Central Highland provinces are covered; and ii) all implementers use a standardized survey tool; whether this is from GCP or another party is of less importance, as long as it results in consistent and mutually comparable data. This would allow for better informed management and policy decisions at a level above the individual project. We recommend integrating these requirements as a pre-requisite for accessing project funding.

Although the variables collected with the GCP tool were the most complete in terms of what is needed to conduct this type of study, gaps remain. One notable issue is that only trees generating a revenue stream (or have the potential to do so) are recorded. Trees without direct marketable produce, such as the trees that pepper vines grow up against or those that form windbreaks, were not included, yet they contribute to carbon sequestration. We recommend tracking these trees' species names and numbers planted in a given year.

We found some differences in Lam Dong between Kinh and ethnic minority farmers, and one of the research questions centered on how these groups perform relative to one another. Not all partners had this data available, nor did data from GCP. Integration of a question on ethnicity can reveal more.

Across all datasets numerous outliers were detected, many of which can be avoided by implementing a simple sense-check algorithm in a data collection app, whether that is the GCP tool or some other application. We recommend such checks on key variables including planting density, fertilizer use, yield, revenue, and cost of production. The idea is to let the app issue a warning to the enumerator if an entered value exceeds a certain threshold on a per ha or per Mt GBE basis. The enumerator should still be able to store and proceed to the outlying value, some outliers are real after all, but we expect such warnings to reduce incorrect observations, e.g. with yields in excess of 15 Mt GBE/ha or planting densities of >7,000 trees/ha.

Regularly occurring fixed names can vary a lot in the data sets. For fertilizer, commune, and village names it makes sense to standardize as much as possible and make use of pre-filled menus that allow enumerators to select options rather than type in free text.

All partners, irrespective of the data collection tool they use, do not consistently track units in which data is reported. This wouldn't necessarily be an issue if all farmers report the same variables in the same units, but this is not the case. Therefore, we recommend letting enumerators enter units for all survey questions that pertain to volume and value.

Some data sets had only single-entry options for each farmer in a given season to report on the biocides they had used. Farmers who spray biocides often spray more than once per season and often with different types of biocides. Allowing multiple entries to be made for this would better capture the range of farm management practices.

If greater reliability of carbon footprints is desired, then asking farmers about the land use on their plot, prior to them running it as a coffee farm would be advisable, at least where farms were established less than 20 years ago. This could be done with a number of simple categories such as: primary forest, secondary forest, other perennial production, arable production or grass/shrub land.

Service delivery data was severely lacking in all cases; even the partners that could provide some were not able to provide a complete picture. If partners wish to better understand the effects of their interventions on the farmers in their supply chain, then this issue needs to be addressed. Ideally, a sector-led development, similar to the GCP tool, might make sense. If a sector-led initiative is not possible, then at least JDE and IDH could set a standard for their partners and require them to keep adequate records in a consistent manner. Currently, we understand which aspects of farm management could be tweaked to reduce carbon emissions, but in the absence of detailed service data, we cannot ascertain the effectiveness of interventions that partners provide to farmers.

6.2 Interventions

While data on specific interventions provided to farmers was very limited, we do identify two main drivers of emissions and hence levers through which emissions could be reduced. On these we provide some recommendations on interventions.

6.2.1 Optimizing nutrient management

Programs that seek to lower the carbon footprint of coffee can in our assessment best focus on optimizing the use of fertilizer. We have observed a reduction in fertilizer use over the past five seasons, likely as a result of a combination of project interventions and lower coffee prices. For a majority of farmers, further improvement is possible. The objective can then be to first move to the conservative benchmark of optimal nitrogen fertilization rates of around 120 kg N/Mt GBE, but we believe further reductions are possible without endangering yields. This approach has the added benefit of reducing costs of production and therefore has an inherent economic incentive to encourage farmer adoption. To convince farmers to go towards or below that benchmark, a number of approaches, arranged from inexpensive to more costly, could be deployed:

1. We recommend continuing GAP training sessions for farmers with the inclusion, if this is not already the case, of simple methods on how to adjust fertilizer applications based on the expected yield. Key parameters in this are the content of N, P, and K contained in a kg of fresh cherry (0.5 percent; 0.029 percent and 0.6 percent respectively). Early in the season, just after flowering when coffee cherries are in the pin head stage, farmers can develop a yield prognosis by counting the pin heads on a number of branches, multiply that by the average number of fruit-bearing branches per tree and the number of trees they have. Partners would have to provide farmers with standard values on how many fresh mature cherries are in a kg of harvested coffee. Best to determine this regionally and perhaps by main varieties as these numbers may vary somewhat. In combination with these percentages, the *minimum* nutrient replacement rate can be determined. However, a share of nutrients will not reach the tree because of losses, another unknown share is required to sustain leaf and woody material growth. Among the best performing farmers we see a use of 120 kg of N/Mt GBE. With the yield prognosis the 120 kg benchmark can then be used to determine the *maximum* application rate. If farmers grow more crops than just coffee, a similar approach could be used to account for the nutrient requirements of pepper, durian, etc.
2. Another approach could be to encourage farmers to try different nutrient management regimes out on a sub-set of say 30 coffee trees on their farm while keeping the remainder under normal management. These would then be harvested separately and their yield per tree compared to the remainder of the farm that is under normal management.
3. Soil testing can help, but soil conditions within a field can vary greatly and a multitude of samples are often required to obtain a clear picture. Furthermore, confidential analysis of Agri-Logic on soil-test derived fertilizer recommendations in 2016 for one of the partners in this project indicated that such advice can miss the mark by a wide margin. We advise caution and the use of double-blind samples to determine if laboratory results are reliable or send a number of identical samples to different laboratories.
4. Data-driven approaches such as the Farmer Field Book (FFB³) could play a role as they objectively quantify differences in investments and returns among groups of farmers who operate in the same geographical area. There are usually a number of farmers in an area who outperform the majority. Learning from better performing peers how to improve management can be more convincing than from relative outsiders.

³ Disclaimer: Agri-Logic owns the FFB software and guides clients in its implementation.

6.2.2 Diversification

Increasing diversification via intercropping is an important strategy to enhance carbon sequestration, but this is an intervention that requires longer-term investment. From the data we have, it is not clear if farmers outside certain districts in Dak Lak and Dak Nong are keen. In the long run the footprint reduction effect of increasing diversification is likely greater than from optimizing nutrient management, but the latter has the added benefit of short-term reduction of production cost and is therefore probably an easier sell to farmers. Current recommendations from some of the partners in this study are for farmers to move to a maximum of 80 non-coffee trees per ha. We do see uptake of this in the data, at least among the partners who promote this *and* keep track of tree planting activities; not all do. We suggest continued monitoring. Although the sequestration effect may be more limited and farmers would not move out of the monocrop category⁴ with this planting density, doing so is not a goal in and of itself. Rather, the option to generate additional cashflow is an important one and linked to that, somewhat greater yield resilience among farms with greater levels of diversification. Investments in further market development for the intercropped tree species, such as durian, avocado, pepper, etc. would also help to provide additional economic incentives for farmer adoption.

6.3 Considerations for further research

The current study has number of limitations that future studies can address:

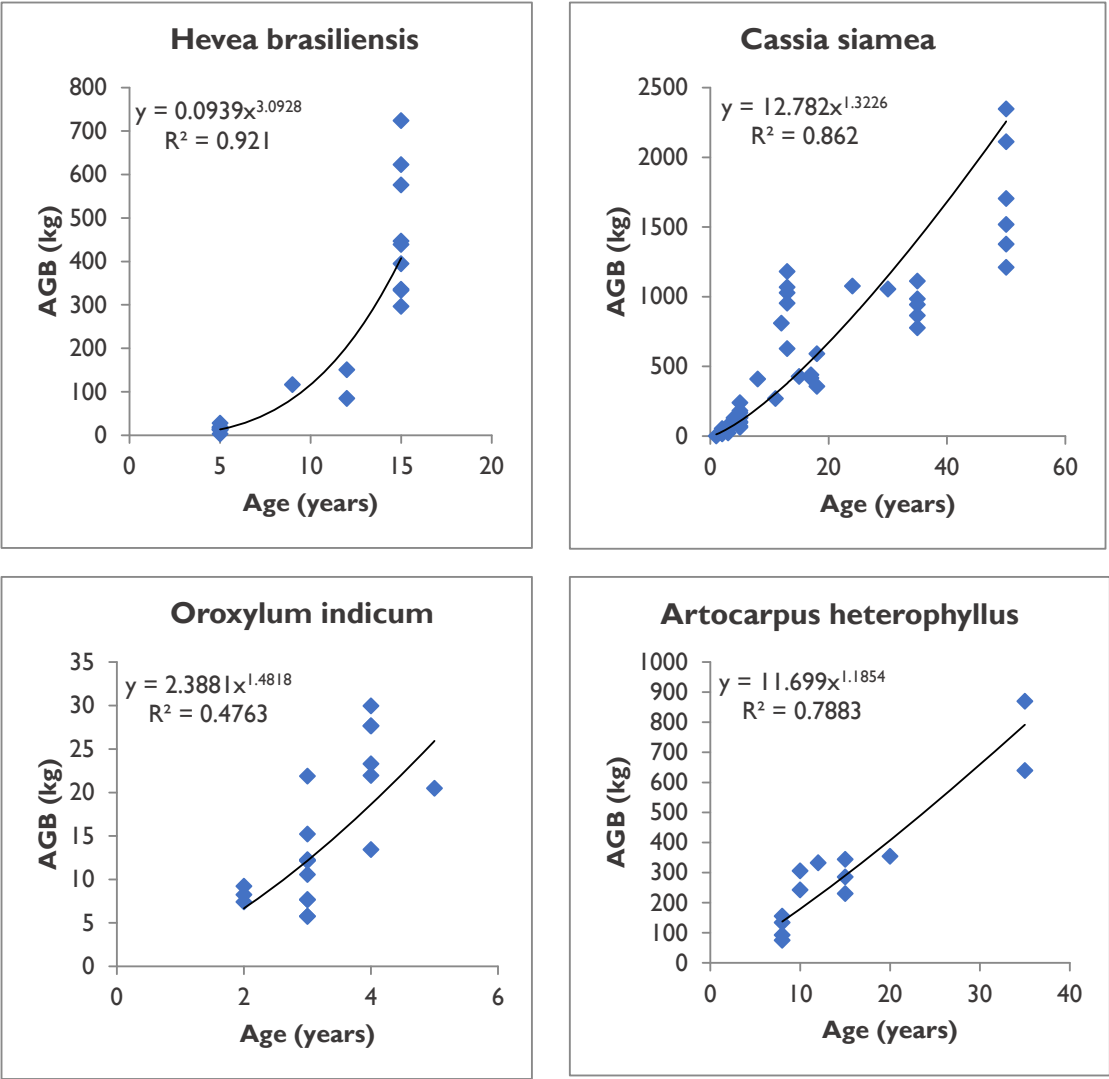
1. The sample of tree measurements that we used to build the species-specific models to estimate mass from age would ideally be strengthened by adding measurements. This should consider both the species we have currently modelled with a relatively low number of observations (Annex 1), as well as species farmers start growing that are not currently covered.
2. We currently estimate Above Ground Biomass as the main contributor to carbon stocks and sequestration, but other carbon pools, such as belowground (root) biomass, are also important. Research-based approaches that take whole tree measurements are both destructive and costly. We do not think that in this context the effort is worth the return. However, more study on how Below Ground Biomass could be modelled would be worthwhile to investigate. Using standard values from literature is a possibility, but this may obscure significant differences between species.
3. Soil organic carbon is not factored into our model and this would be something that future studies can include. Changes in soil organic carbon are difficult to measure over short time frames, as significant changes may take years to materialize. Therefore, this type of study might perhaps best be done at research stations where soils can be under controlled management for longer time spans.
4. Emission factors for fertilizer used in all emissions studies rely on a narrow base of literature, mostly from western locations. This is fine for inter-origin comparisons, but ideally, fundamental research into emissions from fertilizers in tropical soils should be conducted.
5. It is outside our scope of work to recommend optimum species mixes for different farms in different locations, but continued work on this by applied research institutes such as the Western Highlands Agriculture and Forestry Science Institute (WASI) in Dak Lak seems advisable. Ideally, effects of new plantings on local markets are considered in this work. Recommendations that work biologically *and* economically are required.
6. In the current study we only had access to data from farmers involved in a project. In the absence of a control group, it is difficult to attribute change we observed in the correct proportion to project interventions and changing market conditions over the same time frame. For project implementers it can be challenging to collect data from farmers they do not directly work with. In this light, we recommend JDE and IDH to consider if and how they could in future projects build in a component that seeks to track how non-project farmers fare. Alternatively, cohort analysis could be used, but only if and when adequate service delivery data is available, and farmers are subjected to different levels of services (both over time and in frequency).

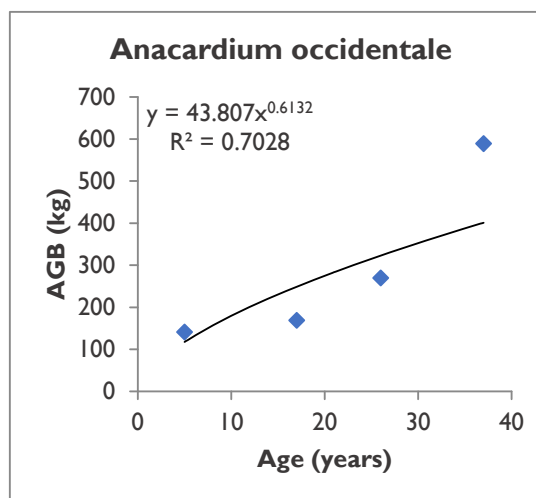
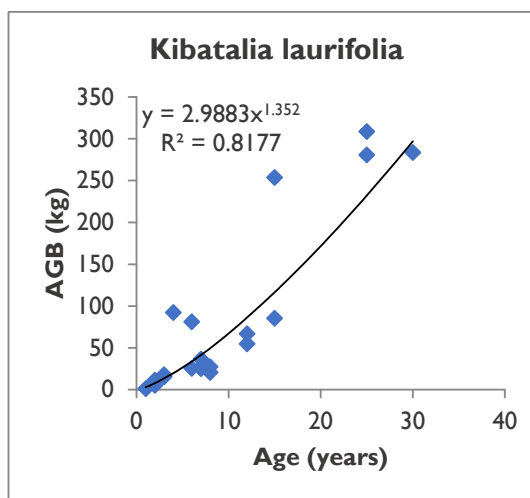
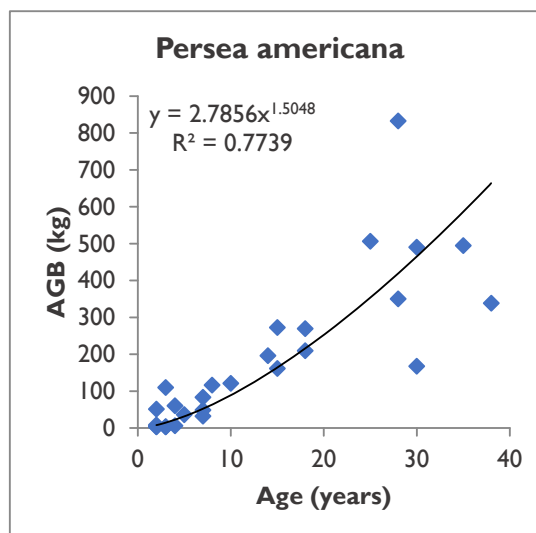
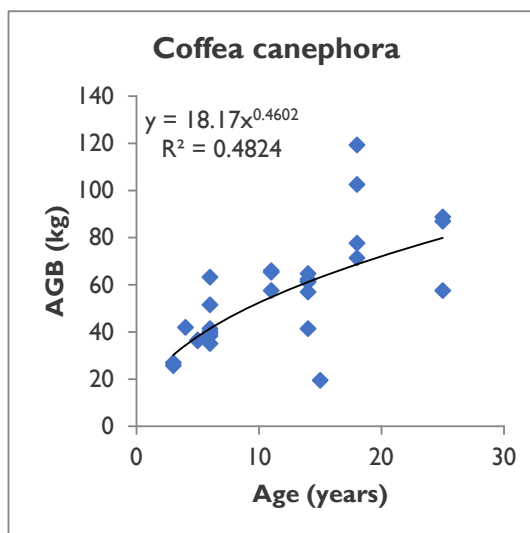
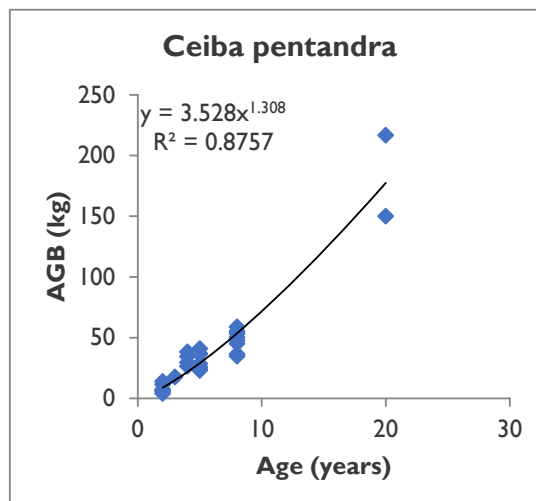
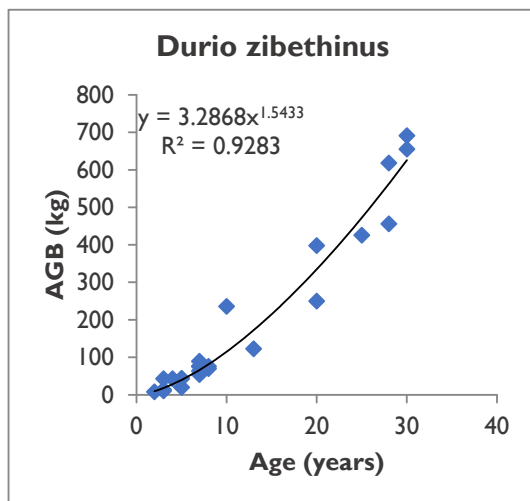
⁴ Defined in this study as <15% non-coffee trees.

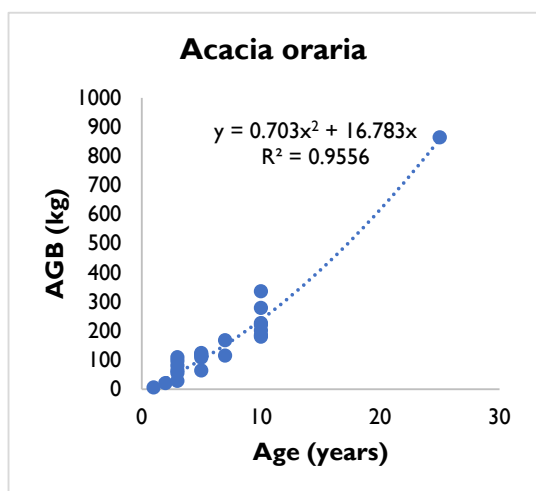
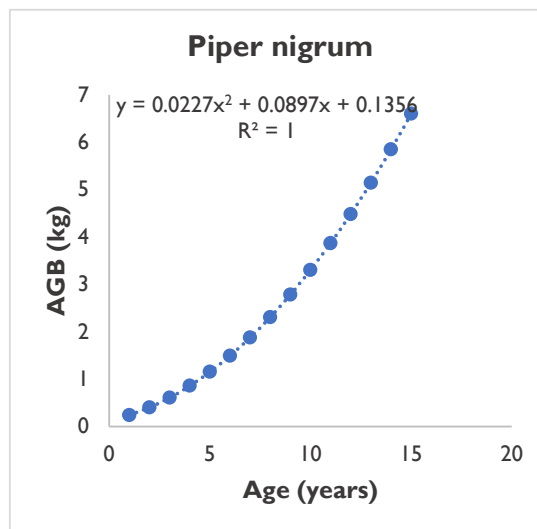
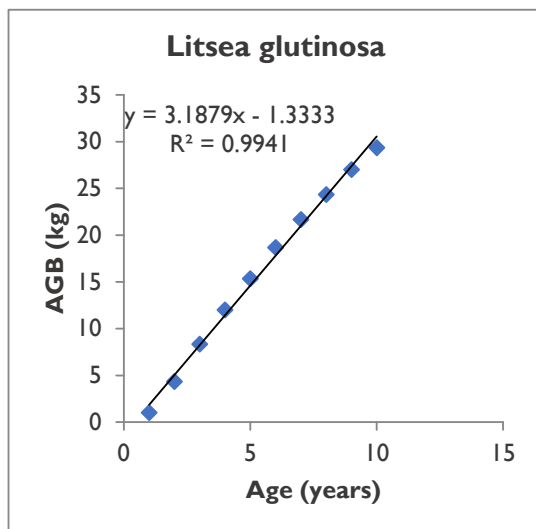
References

- ASEM Connect, 2019.
<http://asemconnectvietnam.gov.vn/default.aspx?ID1=2&ZID1=8&ID8=93012#:~:text=Coffee%20export%20revenue%20for%20Vietnam,tons%2C%20valued%20at%20%24258%20million>. Accessed 6/10/2020
- Bunn C, Lundy M, Läderach P, Fernández P, Castro-Llanos F. 2019. Climate-smart Coffee in Uganda. International Center for Tropical Agriculture (CIAT), Cali, Colombi
- Environdec 2013. UN CPC 01610 Green Coffee.
- Gro-Intelligence 2016. <https://gro-intelligence.com/insights/articles/vietnamese-coffee-production> Accessed 2/12/2020
- Huy, B. 2009. CO₂ Sequestration estimation of *Litsea glutinosa* species in agroforestry model of Litsea and Cassava in Mang Yang District, Gia Lai Province of the Central Highlands of Vietnam.
- ICO 2018. <http://www.ico.org/documents/cy2018-19/icc-124-9e-profile-vietnam.pdf>
 Accessed 6/10/2020
- ICO 2019. <http://www.ico.org/documents/cy2018-19/icc-124-9e-profile-vietnam.pdf> Accessed 6/10/2020
- ICO 2020. <http://www.ico.org/prices/ml-exports.pdf> Accessed 6/10/2020
- IDH, 2017. https://www.idhsustainabletrade.com/uploaded/2019/06/170725_FFB-report-ISLA-program-updated-2016-17.pdf Accessed 10/12/2020
- IDH 2019. https://www.idhsustainabletrade.com/uploaded/2019/03/The-carbon-footprint-of-Vietnam-robusta-coffee_2019.pdf
- IDH 2019. https://www.idhsustainabletrade.com/uploaded/2019/06/190514_FFB-report-ISLA-programme_Final.pdf
- IPCC 2006. Guidelines for National Greenhouse Gas Inventories.
- K. Kandianan et al 2002. Allometric Model for Leaf Area Estimation in Black Pepper (*Piper nigrum* L.) J. Agronomy & Crop Science 188. 138-140.
- Malimbwi R.E., Eid T., and Chamshama S.A.O. 2016. Allometric Tree Biomass and Volume Models in Tanzania. Chapter 11 presents cashew nut trees (*Anacardium occidentale*) biomass and volume allometric models.
- Matthew Brander et al, August 2011. Technical Paper Electricity-specific emission factors for grid electricity:
<https://ecometrica.com/assets/Electricity-specific-emission-factors-for-grid-electricity.pdf>
- Nguyen-Duy, N., Talsma, T., Nguyen, K. T., Do, T. C., D'haeze, D., & Laderach, P. 2018. Carbon assessment for Robusta coffee production systems in Vietnam: a case study in Dak Lak. International Center for Tropical Agriculture (CIAT). Hanoi, VN. 22 p.
- Rachawat, T., et al 2018. Carbon and water footprint of Robusta coffee through its production chains in Thailand. Environment, Development and Sustainability, 2020, 22, pp.2415-2429.
- Rikxvoort, H., Schroth, G., Laderach, P., and Rodriguez-Sanchez, B. 2014. Carbon footprints and carbon stocks reveal climate-friendly coffee production. Agronomy for Sustainable Development, Springer Verlag/EDP Sciences/INRA, 2014, 34(4), pp.887-897.
- SCC. no date. https://www.sustaincoffee.org/assets/resources/CountryProfile_Climate_Coffee_ALL.pdf Accessed 7/12/2020
- UNHDE 2019. <http://cloud.csiss.gmu.edu/dataset/3cb544a9-9d04-4f54-94e2-93230efd8ceb> Accessed 7/10/2020
- USAID Green Invest Asia 2020. <https://greeninvestasia.com/> Accessed 6/10/2020
- USDA FAS 2020.
https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Coffee%20Annual_Hanoi_Vietnam_05-15-2020 Accessed 6/10/2020
- VCC&C 2019. Personal communication.
- Vossen, van der, H.A.M. 2005. A critical analysis of the agronomic and economic sustainability of organic coffee production. Expl Agric. (2005), volume 41, pp. 449–473 Cambridge University Press

Annex I: Above Ground Biomass models







Annex 2: Summary table of main findings

	Monocrop	Medium-diversified	Highly Diversified
	< 15% non-coffee	15 – 30% non-coffee	>30% non-coffee
Coffee trees (#/ha)	1,008	996	882
Non-coffee trees (#/ha)	10	309	940
Proportion of sample population (%)	66%	7%	27%
Yield - Mt GBE/ha (5-year average)	2.92	2.79	2.63
Emissions – total (Mt CO ₂ e/Mt GBE)	1.56	0.89	0.83
Fertilizer	1.47	0.79	0.68
energy	0.09	0.10	0.15
Carbon stock (Mt CO ₂ e/ha) 2019/20	34.0	42.2	45.5
Coffee	34.0	38.7	38.0
Non-coffee	0.04	3.50	7.5
Carbon footprint Mt CO ₂ e/ha (3 years, range)	1.01 – 4.76	0.87-2.93	0.28 – 1.09
Average (Mt CO ₂ e/ha)	1.56	1.49	0.99
Percent of farms with negative footprint	8%	15%	32%
Revenue (share) Coffee	97%	83%	69%
Revenue (share) Non-coffee	3%	17%	31%
Profitability - million VND/ha (3-year average) (USD)	51.1 (\$2,222)	40.3 (\$1,752)	62.8 (\$2,730)