# Sustainable Intensification of UK Agriculture: Concepts and Application


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# Table of contents

## *ii. Abstract*

Sustainable intensification is a goal for 21st century agriculture that requires producing more food with less damaging outputs, including greenhouse gas emissions. This research observes the relationship between the inputs, practices and characteristics of cereal farms and the outputs produced. The activities of 336 cereal classified farms from the 2017 Farm Business survey were analysed using linear regression. Data on commercial outputs were taken directly from the survey. Greenhouse gas output data was derived using the Sustainable Intensification research Platforms carbon equivalency coefficients. Data on activity expenses and survey questions on specific techniques were used to observe practices. Farm location codes were used to observe the locational characteristics. Data collected by the University of Nottingham, on Land Grade Classifications, were used to add further detail to the locational characteristics. Analyses were performed at three different levels: total farm level output, per hectare output and per tonne output. At each level of measurement higher inputs generally led to higher outputs. Data on the specific techniques of green manure usage and precision farming proved to be significant. The former of these reduced emissions and the latter increased them, but also increased yields. This is despite both methods purporting to reduce emissions. These were only observable at a per hectare and per tonne level. Inputting data on location and on farm characteristics provided limited results. This showcased the limitations with the chosen carbon equivalency calculator and correlated with other studies using the same one. Although limitations were observed with the dataset, coefficient and with the scope of the research, it was found that similar methods could be used by policymakers to analyse trends in greenhouse gas mitigation and for individual farmers to improve resource use efficiency.

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## *iv. Abbreviations*

| **Abbreviation** | **Definition** |
|---|---|
| GHG | Green-House Gas |
| UK | United Kingdom |
| CEH | Centre for Ecology and Hydrology |
| JCA | Joint Character Area |
| SIP | Sustainable Intensification research Platform |
| IPCC | Inter-continental Panel on Climate Change |
| CPP | Crop Protection Products |
| SOM | Soil Organic Matter |
| SOC | Soil Organic Carbon |
| CO2 | Carbon dioxide |
| N2O | Nitrous oxide |
| NO3 | Nitrate |
| NO2 | Nitrite |
| NI | Nitrification Inhibitor |

# 1.0 Literature review: Greenhouse gas emissions from UK arable agriculture

## 1.1 Introduction

Climate Change is one of the most discussed and impactful environmental topics of recent history (Jakučionytė-Skodienė et al., 2021). This is due to its damaging impacts on weather and other environmental conditions (Kertesz and Madarasaz., 2014). The reduction of greenhouse gas (GHG) emissions is required to halt climate change and stop the increase of global temperatures (Zheng et al., 2019). A GHG is any gas that can absorb infrared radiation or heat energy. In the case of the green-house effect, this energy is sourced from the Sun and reflected into the atmosphere from the Earth's surface (Mann, 2019). GHGs hold the energy in the atmosphere, maintaining the Earth's temperature (Denchak, 2019).

Increasing the quantity of GHGs in the atmosphere increases the quantity of heat energy trapped, also increasing the Earth's temperature (Denchak 2019). This rise changes the climate activities of the world, impacting weather patterns and making them more volatile (Mann, 2019; Denchak, 2019). The concentrations of GHGs has varied substantially over the Earth's history; this change has been controlled by a variety of factors (Mann, 2019). However, the steady increase following the 'Industrial revolution' has led to the conclusion that human activity is largely responsible for the current level of emissions and the rising global temperature (Mann, 2019; Denchak, 2019).

Agriculture is responsible for the production of all three of the major GHGs, which are carbon dioxide, methane, and nitrous oxide, producing over 30% of total global emissions (Gilbert, 2012). Agriculture has a unique position as being both an emitter of GHGs through production yet is also a mitigator of them (Chirinda et al., 2011). This is due to the cyclical nature of the emissions, where the output and intake of GHGs form part of a recurring cycle (Lynch et al., 2020).

### *1.1.1 Search method*

This literature review focuses on the factors that change GHG output through its mechanism of soil microbial activity, such as the climate, weather, and physical factors What follows is a literature review outlining these factors and what is currently known about their effects. The literature reviewed will primarily be confined to articles concerning UK and European agriculture specifically, to provide a level of relevance to the research being pursued and homogeneity among the results. Searches were conducted using the databases 'Sciencedirect' and 'JSTOR' between October and December 2020.

### *1.1.2 Greenhouse Gases*

Carbon Dioxide can take over 200 years to breakdown in the atmosphere, once emitted (Lynch et al., 2020). Carbon dioxide's ability to cause a greenhouse effect is the benchmark by which other gases are measured (Lynch et al., 2020). In the context of agriculture, the quantity of carbon stored within soils is as much as three times higher than is found in the atmosphere (Cho, 2018; Ontl and Schulte, 2012).). Importantly, a third of this is within the top 20cm, meaning that using this land can have a huge impact on its carbon storage (Pries et al., 2018). This is unlike the majority of industrial GHG emissions, where carbon that has been stored for millions of years is released through the burning of fossil fuels, with no mechanism for its breakdown and storage, with carbon dioxide being uniquely long-lived (Halbouty, 2003; Lynch et al., 2020). This has occurred by dead organic matter that is broken down by soil microbial life as a part of the carbon cycle (Chirinda et al., 2011). At the soil stage of the cycle, the components of this breakdown are known as soil organic matter (SOM), with the carbon content being specifically referred to as soil organic carbon (SOC) (Heintze et al., 2017).

Methane has an atmospheric lifespan of 18 years and has 27 times the warming potential as carbon (Lynch et al., 2020). Within agriculture, its primary source is from livestock production, which is the source of half of all methane emissions in the UK, with the largest contributor of methane output coming from enteric fermentation, from flooded rice production and ruminant digestion. With regards to arable agriculture, manure management is a significant contributor (Heilig,1994), making up 13% of agricultural methane emissions in 2014 (DEFRA, 2014). There is criticism over the measurement of methane in comparison to other GHGs. Methane is known as a short-lived climate influencer, as opposed to the long-lived gases; nitrous oxide and carbon dioxide (Lynch et al., 2020).

The final gas, nitrogen, is the most important when it comes to arable agriculture. It remains in the atmosphere for around 114 years (Thomson et al., 2012) and has 298 times the greenhouse potential as carbon (Butterbach-Bahl et al., 2013). Because of this, it accounts for 10% of the overall GHG effect, despite making up 0.3% of physical emissions (Thomson et al., 2012). 50% of global nitrous oxide emissions are from agriculture and there has been an upward trend in emissions over the past 140 years (Thomson et al., 2012), increasing by over 19% since pre-industrial times (Butterbach-Bahl et al., 2013).

### *1.1.3 GHGs in UK Agriculture*

Agriculture is responsible for around 10% of UK GHG emissions (DEFRA, 2019). Agricultural land has been intensifying and declining in area, though not expanding into untouched ecological territory (Dallimer et al., 2013; Norton, 2017). This contrasts with many other countries, whose agricultural land has expanded at the expense of land high in SOC and vegetation like rainforests (FERN, 2017).

In the UK, 10 billion tonnes of carbon are estimated to be stored in soils, this has reduced and is currently reducing due to intensive practices (Environment Agency, 2019). In 2019, the UK environment agency found that arable farming has caused a loss of between 40 and 60% of SOC, reducing the amount of carbon stored (Environment Agency, 2019).

Within the UK, over 70% of nitrous oxide emissions are from the agricultural sector through fertilizer use (DEFRA, 2019), making it the most impactful emission from arable agriculture.

Management of this output has a commercial gain as fewer emissions lead to more nitrogen available for plants, resulting in higher yields and more income. However, this has not been enough of a motivational factor to curb emissions, with rates still rising, peaking at 79% of the UK's nitrous oxide inventory in 2016 and 75% in 2019, despite the average of 70% per year (DEFRA 2016, 2019).

An obvious reduction technique would be to limit the use of manures and fertilizers. However, current crop yields and levels of food security are fuelled using nitrogen fertilizers, supplemented by farmyard manures. An increasing need for food will also increase demand for fertilizers (Chirinda et al., 2011). Hence, solutions need to be found that reduce the emissions without compromising the yields needed.

## 1.2 Soil Microbial activity

The primary sources of each of the GHGs are through soil microbial activity. Both the carbon and nitrogen cycles rely on soil microbes to progress through the soil stage (Oertel et al., 2016; Chirinda et al., 2011). The breakdown or output of methane also relies on microbes (Chadwick et al., 2011).

Specifically, carbon dioxide emissions from agriculture are caused by respiration of soil microbiota, alongside production emissions from the usage of fossil fuels (Cho, 2018). Carbon is absorbed by living things, entering the soil through root systems or when they die and decompose. When the microbiota has ample access to oxygen, they convert the stored carbon into carbon dioxide. More exposure to oxygen leads to higher outputs of carbon dioxide (Oertel et al., 2016).

Methane's relationship with soil microbiota is different. Under aerobic conditions methane can be broken down by soil microbiota, contributing to the soils carbon content (Chadwick et al., 2011). However, if there is not enough access to oxygen for this reaction, anaerobic respiration will take place, emitting methane into the atmosphere. Microbial oxidation in soils is the only currently known sink for removing methane from the atmosphere (Tveit et al., 2019).

The most prominent GHG produced by arable agriculture, nitrous oxide, is also dependant on soil microbiota. The nitrogen cycle starts when atmospheric nitrogen is converted into ammonia by bacteria within the soil (Senbayram et al., 2019). This is then broken down into nitrate (NO3), by way of nitrite (NO2), which is an inorganic compound that plants can utilise for growth or converted into atmospheric nitrogen through the process called denitrification, also accessible to plants (Senbayram et al., 2019).

For the nitrogen taken up by plants, it is then either consumed by other organisms or decomposes. This decomposition is again performed by bacteria, along with fungi, returning the nitrogen to the soil. If the plant is consumed the nitrogen will be excreted by the organism, through urine or manure as examples. The remaining nitrogen will also return when the organism dies and is also decomposed. The micro-organisms performing these functions all respire, contributing to the carbon cycle also (Taft et al., 2018).

Nitrous oxide is a by-product of the conversion of ammonia into nitrate, also known as nitrification (Butterbach-Bahl et al., 2013). Both these processes are carried out by bacteria within the soil. During the nitrification processes, oxygen is required to produce nitrate and nitrite. If it is not present the by-product of nitrous oxide will be produced at a higher rate (Dong-Gill et al., 2013). This has a lower oxygen requirement.

Nitrous oxide can also be produced through denitrification, the given name of the conversion of nitrate into atmospheric nitrogen (Martens, 2005). Under anaerobic conditions atmospheric nitrogen is favoured; whilst nitrous oxide will be favoured when there is oxygen availability (Martens, 2005).

Modern agriculture synthesizes organic nitrogen sources in the form of fertilizer, to be applied to soils and converted, artificially adding nitrogen into the cycle. It can also be a by-product of the process of denitrification, when nitrate is converted or reduced into atmospheric nitrogen, again performed by soil bacteria (Butterbach-Bahl et al., 2013). Limited oxygen increases the rate of denitrification, causing the conversion of more atmospheric nitrogen and nitrous oxide (Oertel et al., 2016).

### *1.2.1 Soil Conditions*

Soil microbial activity is the primary mechanism responsible for arable GHG emissions, as noted in the contexts of the carbon, nitrogen, and methane cycles.  Activities performed that affects the output of land based GHGs are because of changing the conditions of the soil's microbial life. Studies investigating methods into reducing GHG emissions found that the soil and weather conditions changed the behaviour of the microbes and therefore GHG emissions (Taft et al., 2018). The microbes responded to external factors such as temperature and rainfall, or internal factors including soil types and carbon/nitrogen ratios (Taft et al., 2017; Taft et al., 2018; Norberg et al., 2016). These can then be exacerbated by management practice (Taft et al., 2018; Oertel et al., 2016).

The UK has over 700 unique soil types and therefore many different environments that microbial activity occurs within (Countryside, 2019). These fall into several broad categories: Sand, Silt, Clay, Loam, Peat, and Chalk (RHS, 2021). These are based upon the size of the particles formed, the methods of its formation, and the raw materials it was formed from, for example chalk (RHS, 2021). Sand is made up of particles that are between 0.05mm and 0.2mm, Silt particles are between 0.05mm and 0.002mm, with Clay particles being below 0.002mm (RHS, 2021). A loam soil has an equal amount of all three particles (RHS, 2021). Peat soils have a high presence of SOM, whilst Chalk soils have chalk stones and particles within them (Soil Association, 2021; RHS, 2021). These are given distinction due to the uniqueness of their composition, for example the high alkalinity that chalk soils inherently have (Soil Association, 2021; RHS, 2021).

The actual type of a soil will sit somewhere between these categories, for example a sandy loam soil, will have all three particle sizes, but with a higher quantity of sand. Soils are often given unique names to describe their specific characteristics. For example, the most common soil type in Cornwall is known as 'Shillet' which is also a Sandy loam (Cornwall Council, 2020). The structure and texture of the soil can also have a prominent effect on the activities within it. Different soils have different attributes that benefit crop yield (Soil Association, 2021) and the same goes for GHG emissions.

Soils are also graded by quality, which is known as an Agricultural Land Grade (LRA, 2021). These range from grades 1-5, with the most common category being grade 3 or 'good to moderate' quality. These grades are based upon the limitations of the land for growth. They Incorporate both physical and chemical limitations that affect the ability to grow crops on them (LRA, 2021).

Thomson et al. (2012) found that the lack of specific enzymes, known as nitrous oxide reductase, causes a reduction in the denitrification rate. This enzyme is dependent on soil bacteria producing it (Thomson et al., 2012). Bacteria containing a specific gene (nirK) was found to be responsible for this. Overall, Thomson et al. (2012) found that nitrous oxide production is dependent on soil microbial activity, with the environmental conditions affecting the output.

## 1.3 Climatic factors

### *1.3.1 Temperature*

Temperature is linked to metabolic and respiration rates in living things (Clarke and Fraser, 2004) inclusive of microbial activity. A study observing the GHG output of peat soils and comparing it to the results predicted by emissions factors found a positive relationship between temperature and carbon dioxide output (Taft et al., 2017). Specifically, both air and soil temperature were highlighted. Whilst this is a scenario with peat soils specific conditions, it does point to temperature as being a factor in certain environmental conditions (Taft et al., 2017). This is of particular interest, given that the emissions factor used, the Intergovernmental Panel on Climate Change's standard (Penman et al., 2017), did not incorporate temperature (Taft et al., 2017).

Butterbach-Bahl et al. (2013) also found that the process of denitrification can be very sensitive to temperature changes. This study was based on more generic soils and noted the coupling of the carbon and nitrogen cycle. Respiration induced by increased temperature causes a depletion in soil oxygen content. This results in an increase in the instance of denitrification, causing more nitrous oxide to be emitted (Butterbach-Bahl et al., 2013). This process being directly linked to temperature points to it being a significant influence on GHG outputs.

It is documented by several sources that temperature and water overlap in their effects, with respect to their influence on GHG emissions, especially carbon dioxide and nitrous oxide (Shang et al. 2020; Krol et al. 2016; Oertel et al. 2016). Both affect the microbial activity in the soil, with higher temperatures increasing activity (Dawar et al. 2020). This was noted in a study observing the annual emissions, criticising studies or models that did not account for the non-linear nature of emissions across a whole year (Shang et al., 2020). They found that within the UK water is the more dominant factor. Temperature does account for some of the variation, especially with carbon dioxide output, reinforcing previous observations of this relationship (Shang et al., 2020). Whilst water was the more dominant factor in the previous study, temperature still held influence. The study was based on testing a specific emissions factors 'ΔEF' in four climatic zones, using the labels 'warm', 'cool', 'moist' and 'dry'. Moist areas had an overall higher level of emissions, with mean results of 0.10 and 0.8 ΔEF for the 'warm/moist' and 'cool/moist' areas. Whereas the 'warm/dry' area had a reading of 0.1 ΔEF. A difference was noted based on the temperature, but its significance was lower than moisture (Shang et al., 2020).

The observation of moisture or rainfall overriding temperatures influence is supported by Krol et al. (2016). This study investigated reducing nitrous oxide emissions across different soil types, with manure application. Temperature was found to have a significant influence, though only with well-drained soils, where water became less of a factor (Krol et al., 2016).

### *1.3.2 Soil Moisture and Rainfall*

Shang et al. (2020) and Krol et al. (2016) referred to the influence of water on GHG emissions, in forms such as rainfall or soil moisture. Water limits oxygen access within soil, changing how well respiration can be carried out (Oertel et al., 2016; Fan et al., 2021). This changes the speed and outcome of any reaction. For example, in the nitrogen cycle nitrous oxide is produced as opposed the more desirable Nitrite and Nitrate, because of its lower oxygen requirement (Fan et al., 2021). For manures, methane is produced in higher quantities due to lower aerobic breakdown needed to mitigate this (Fan et al., 2021).

By observing SOC as a method of reducing emissions, Sanchez-Martin et al. (2010) found that application of water to soil increases carbon dioxide and nitrous oxide output. The carbon dioxide increase was very short-lived. This supports previous studies, pointing to temperature and not rainfall or soil moisture as being the factor with more influences over carbon output (Krol et al., 2016; Shang et al., 2020).

Soil moisture and rainfall have been identified as significant factors for nitrous oxide (Abalos et al., 2016; Oertel et al., 2016; Krol et al., 2016; Fan et al., 2021). Despite previous studies not being conducted within the British Isles, a study based in Ireland found that high nitrous oxide emissions always follow rainfall (Krol et al., 2016). Whilst the study aimed at identifying if water filled pore spaces (WFPS) in soil were a significant influence on emissions, it was instead concluded that rainfall was a more significant factor (Krol et al., 2016). It also documented that the period of emissions following rainfall were always longer on lesser draining soils and noted that this is consistent with other studies on the same subject, such as Mosier et al. (1998), Dobbie and Smith (2001), Luo et al. (2013) and Krol et al. (2016). Although WFPS in soil were a less significant influence than rainfall, they did provide explanation for some of the emissions. For example, the only time of year that WFPS had significant influence was in the spring, where it was higher than other times of year at 60%, 82% and 71% averages at the three sites. In the summer (averages of 44%, 48% and 57%) and autumn (53%, 55% and 74%) no significant relationship was found. Drainage and rainfall were explaining the increase in soil moisture at the third site and the behaviour of nitrous oxide emissions. This signifies that soil moisture levels can affect GHG emissions, but that rainfall is the stronger factor, increasing GHG emissions (Krol et al., 2016).

Other studies have explored increasing the overall soil moisture to affect emissions. Taft et al. (2018) proposed changing soil moisture through raising the water table, or the level at which groundwater sits beneath the land surface, to reduce GHG emissions from organic soils. Whilst it was determined that this may not be a practical process, it did prove to be an effective method of reducing soil respiration (Taft et al., 2018). It noted a balance with nitrogen, where dramatically increased water could act as an inhibitor for microbial life (Taft et al., 2018). This has the effect of increasing the efficiency of nitrification. Partially raising the table to 15cm below the surface resulted in higher emissions of nitrous oxide than the control (at around 30cm below the surface) or bringing the table up to the surface.

Overall, it appears that a higher soil moisture content can lead to more efficient nitrogen fixation. However, soils that experience intermittent/partial wetness or rainfall is less efficient, with anaerobic conditions leading to higher nitrous oxide output (Taft et al., 2018; Krol et al., 2016.) This study also explored the effects of tillage, activity which maintains or prepares soil for the plant, through activities such as ploughing, sub-soiling or discing. These activities cause soil exposure which increase aerobic activity (Taft et al., 2018). These had little effect on emissions, but this could be due to the very wet conditions offsetting any increase in soil aerobic activity caused by tillage, as observed by Krol et al. (2016) and Taft et al., 2018.)

This is supported by other studies, such as Abalos et al.'s (2016) analysis of rainfall effects on nitrous oxide emissions within semi-arid conditions. According to Abalos et al. (2016) soils with low moisture have higher rates of nitrification but produce more nitrous oxide proportionally. Low moisture creates aerobic conditions, encouraging nitrification, yet also causing microbial activity to speed up, simultaneously producing more of the needed Nitrites and Nitrates, but also more of the by-product nitrous oxide (Abalos et al., 2016).

Methane is also reactive to soil moisture content. A study into the effects of management practices on GHG output in vegetables found methane emissions were suppressed by either high or low soil moisture (Fan et al., 2021). This can be attributed to the latter enabling aerobic respiration and breakdown (Abalos et al., 2016) not allowing methane emissions, whilst the former condition mitigates all respiration and breakdown, similar to how a high-water table limits carbon dioxide emission (Taft et al., 2018). In either scenario methane emissions are suppressed (Fan et al., 2021).

Fan et al. (2021) also noted the activity of nitrogen across these conditions, where the emissions are only suppressed in one of these scenarios. In the former case the soil is starved of oxygen and the reaction of denitrification produces primarily atmospheric nitrogen (N2). In the latter scenario, there is a higher prevalence of oxygen, promoting the production of nitrite and nitrate (NO2 and NO3). Conditions between these scenarios lead to the production of nitrous oxide (N2O), which sits between the two other scenarios with respect to its oxygen requirement (Fan et al., 2021).

This is corroborated with a project observing the nitrogen flux of three different arable fields and soil types which found rainfall to be the most impactful factor for nitrogen loss in the monitored soils (Webb et al., 2000). Specifically, the largest losses occurred following the combination of rainfall and recent fertilizer application. This is the result of the combination of limited, but not total, unavailability of oxygen, with the prevalence of a nitrogen source (Webb et al., 2000).

The connecting factor between all these scenarios is microbial bacteria (Oertel et al., 2016). The changes that effect the output of land based GHGs are the result of changing the conditions of the soil's microbial life. This can be through starving the microbes of the inputs needed to produce GHGs including reducing oxygen content through rainfall (Webb et al. 2000). Alternatively, it could be inhibiting the metabolic ability to slow down the production, such as occurs when increasing overall soil moisture (Oertel et al., 2016). A high-water table or increasing soil moisture decreases respiration activity and nitrification rate, thus acting as an inhibitor (Oertel et al., 2016; Fan et al., 2021). This changes the overall speed of nitrification, making the reactions more efficient at producing nitrite and nitrate whilst reducing nitrous oxide output. It also reduces respiration and the emission of carbon dioxide (Taft et al. 2018).

Whilst rainfall will slow these same reactions downs it is usually not prolonged enough to drastically change the activity in the soil, e.g., reducing the microbial population or respiration rates (Krol et al., 2016.). Therefore, its main effect is to instantly reduce available oxygen, creating a more anaerobic environment. This then reduces the efficiency of the reaction, producing more nitrous oxide through nitrification, and promoting denitrification which also produces nitrous oxide (Oertel et al. 2016). The Nitrites and Nitrates that are needed for plants require more aeration and aerobic conditions (Krol et al., 2016; Fan et al., 2021).

### *1.3.3 Seasonality*

The aforementioned factors differ greatly by region, but also differ throughout the year. This indicates the season as having an impact on both the total rate of emissions and on the fluctuating rate along the season. The factors associated with the season (rainfall, temperature etc.) will also have an impact.

While studying the efficacy of a model designed to predict carbon activity and comparing its predicted results with field measurements, Flattery et al. (2018) found that respiration rates and GHG output change with the seasons. According to their findings, colder soils inhibit microbial activity and reduce respiration rates, leading to lower carbon dioxide output. This suggests higher GHG emissions are experienced in the Spring and Summer (Flattery et al., 2018).

A separate investigation into tillage systems, on Brazilian Soil, agrees to this as their findings suggest that emissions changed over the course of seasons (Hungria et al., 2009). This 14-year study, which monitored the differing emissions and their dependency of the seasonal activities of specific years, also found that microbial activity and composition vary greatly between climates and regions (Hungria et al., 2009).

This was also found to be the case in the UK climate, with a study observing nitrogen flux from arable soils (Webb et al., 2000). In the UK, wetter seasons lead to higher nitrous oxide output, with winter rain heavily influencing nitrogen loss. The largest losses occurred when fertilizer application and rainfall intersected, creating a scenario perfect for high denitrification rates (Webb et al., 2000).

Taft et al. (2018) also concluded this whilst studying GHG mitigation methods on peat soils; it was noted that emissions were strongly influenced by the weather and the seasons. Their findings revealed that a higher water table overall can slow down or inhibit soil microbial respiration, which increases the efficiency of nitrification, with rainfall being an exacerbator of GHG output (Taft et al., 2018). Rainfalls main effect is to instead reduce oxygen content, causing a higher production of nitrous oxide, as opposed to Nitrite and Nitrate, but not causing the inhibition of microbes. Higher soil moisture is initially less efficient and causes higher emissions, until it reaches a level of inhibition (Taft et al., 2018; Webb et al., 2000).

Production activities such as fertilizer spreading, that occur during the growing season, have less impact. This is because the plants in the ground maintain the soils' structure, reducing the impact that the season has on emissions (Taft et al., 2018) through rainfall and temperature. This points to the growing season as being an influential factor on emissions.

## 1.4 Soil Factors

### *1.4.1 Soil types*

The studies thus far have concentrated on factors external to the soilthat influence the activities of it. Krol et al. (2016) found that soils that have lower drainage ability have a higher and longer peak of emissions following large soil disturbance. Drainage is directly correlated with soil type and structure, with larger particles, i.e., sand particles, having better drainage than alternatives, i.e., clay particles, which hold more moisture (Soil Association, 2021). Thus, a sandy type soil will have more drainage and better ability to tackle emissions than a clay soil, with inherently worse drainage (Krol et al., 2016).

Studies have also noted that sandy soils have consistently lower respiration rates (Norberg et al., 2016; Oertel et al., 2016; Krol et al., 2016.) For instance, Oertel et al. (2016) found that sand type soils respond quicker to nitrification inhibitors and have lower nitrous oxide emissions (Oertel et al., 2016). A further study found that even though noticeable differences in emissions between different soil types were observed, the results were inconsistent, indicating that other factors can override the effects of soil type (Norberg et al., 2016). Webb et al. (2014) investigated the different outcomes of manure application to contrasting soil types, also concluding this. They found that that soil type may be a significant factor, but that activities were more influential than this (Webb et al., 2014).

In the case of slurry application, Heintze et al. (2017) found that the characteristics of the soil were generally more influential than the type of slurry that was being applied. The example given was the high emissions from soils with high organic matter, of both nitrous oxide and carbon dioxide (Heintze et al., 2017). This reinforces the link between the carbon cycle and GHG output of these two gases. In this case no difference was observed with methane outputs (Heintze et al., 2017). This is corroborated by the findings of Oertel et al. (2016) where it was noted that soils with high organic matter had higher GHG emissions, but only when the soil was low on water content. This is backed by Taft et al. (2017; 2018) where research into peat soils high in organic matter concluded that increased moisture could significantly reduce emissions. It has also been noted that methane is seen to be unaffected across different soil types and being more dependent on its application (Heintze et al., 2017).

### *1.4.2 Soil pH*

The acidity or pH is a prominent characteristic in soil, controlling available nutrients and the ease of which organisms survive. It is an influential factor on soil microbial life and therefore on emissions. Although actions can be taken to change pH (Senbayram et al., 2019), this process is costly, and its necessity varies from region to region. For example, sandy textured soils acidify quicker and generally have a lower pH (Lesturgez et al., 2006). The pH affects the ability of living things, such as crop root systems, to grow within soil. It has the same effect on other life forms, including soil bacteria whose population declines at lower pH levels (Smith and Doran, 1996).

One study observing NI performance noted that pH is an influential factor (Bell et al. 2015). Shen et al. (2018) also found pH to be a factor that influenced the results, whilst attempting to create a model of nitrous oxide emission flux from slurry application. It was observed that many current emissions models omit pH in their inputs, despite its influence (Shen et al., 2018).

Senbayram et al. (2019) suggest that liming of acidic soils lead to a decrease in emissions, pointing to pH being a significant factor. Their findings indicate that long-term liming contributes to a reduction in nitrous oxide emissions, but that low quantities of organic Carbon within the soil would disrupt its efficacy. According to their study, in some situations the liming could increase emissions. This allows the conclusion that pH and attempting to control pH were both significant factors, but that the results were variable.

Thomson et al. (2012) observed correlation between soil bacteria containing a specific gene (labelled nirK) and the pH of soil, specifically its link to the content of copper. Soils with both low and very high copper content were found to have high nitrous oxide output (Thomson et al., 2012). It was proposed that this is a result of the nirK containing bacteria being dependant on copper to perform, as well as susceptible to toxicity at high levels (Thomson et al., 2012). However, copper retention in soil is also dependant on pH. Therefore, it is unclear whether the bacteria are reacting to the copper content or the change of pH (Thomson et al., 2012). Either way, pH is an influential factor, whether direct or indirect. (Thomson et al., 2012)

It is apparent that the structure of the soil can directly affect the emissions produced by it. Soil type cannot be changed and varies widely across regions. Farmers are accustomed to adjusting their techniques to create the desired soil conditions that will allow crop growth. The emissions outside of soil disruption are not significantly different between cultivated and fallow fields

(Flattery et al., 2018). Therefore, it is the actions a farmer takes to change soil conditions for the sake of production that is influencing emission (Flattery et al., 2018). To mitigate GHGs and therefore climate change, farmers will need to act in a similar fashion for their soils microbial content, but with the aim of creating the desired conditions for healthy microbial activity (Oertel et al., 2016).

## 1.5 Production Factors

### *1.5.1 Practices*

GHG emissions are controlled by a multitude of interacting external and internal factors, but they are driven by the management choices taken on the land (Taft et al. 2018). Thus far, this review has concentrated on factors a farmer has no control over or must adapt to. However, the practices a farmer takes for their interests of production, also contribute to the GHG output of arable land.

There are no significant differences in the resting respiration rates of cultivated fields when compared to fallow fields but this changes when management activities take place (Flattery et al., 2018; Taft et al. 2018). This is because land use is a key driver of changes in soil respiration from microbial activity (Oertel et al., 2016). For example, tillage or the cultivation of soil increases microbial access to oxygen, increasing its activity and speeding the reaction up (Oertel et al., 2016). This leads to an inefficient reaction and high nitrous oxide output (Oertel et al., 2016). Thomson et al. (2012) concluded that reducing unnecessary tillage in turn reduces GHG output. It was stressed that depending on the circumstances, the use of minimum tillage systems could be equal or more effective than no tillage with respect to emissions (Thomson et al., 2012). The conclusion was reached that optimisation is a more effective solution than minimisation (Thomson et al., 2012).

This idea of soil disturbance being a major contributor to arable GHG emissions is supported by research into variability in mitigation techniques over different soils (Kertesz and Madarasaz., 2014; Thomson et al., 2012; Chadwick et al., 2011; Audsely and Wilkinson, 2014). Soil disturbance through actions like tillage or compaction from machinery has been found to be accountable for as much as 50% of N2O emissions (Henault et al., 2012). This is corroborated by other studies including Audsely and Wilkinson (2014). Their study into general GHG reduction across ten crops found that activities attempting to add SOM may contribute more emissions than it is mitigating (Audsely and Wilkinson, 2014). Straw incorporation was examined as an activity that had a higher output of GHGs than the method was offsetting through the increase of SOM and SOC (Audsely and Wilkinson, 2014).

Systems that significantly reduce their tillage can increase the organic matter content of their soil by as much as 19% (Hungria et al., 2009). Whilst incorporation of debris, such as chopping and integrating straw, may quicken the process of adding SOM (Audsely and Wilkinson, 2014). It is suggested that the impact of further tillage offsets the advantages (Hungria et al., 2009) and that reducing as many interactions with soil as possible was more effective than incorporating organic matter (Audsely and Wilkinson, 2014). However, increasing organic matter in soil makes for a larger sink of carbon and potential encouragement is needed in this area.

Whilst the actions taken certainly have an impact, the timing of these practices also affect GHG output. Seasonality and its consequences, such as rainfall and temperature, are major factors in the efficacy, along with the N2O emissions and efficacy of fertilisers generally (Abalos et al., 2016). This dependency on timing and the weather was outlined in a study observing GHG mitigation methods on peatlands (Taft et al., 2018). Practices occurring during growing systems has less impact, as the plants in the ground maintain the structure through their roots and act as a general sink for carbon (Taft et al., 2018).

Sanchez-Martin et al. (2010) revealed that application of fertilizer led to a surge in N2O emissions, which was more pronounced if it occurred at the same time as rainfall. This is also confirmed by a UK-based study, Webb et al. (2000), who investigated nitrogen fluxes in several arable fields. During the study it was observed that seasons with higher rainfall had higher GHG outputs and specifically that the largest loss of N2O occurs when rainfall and fertilizer application happen together (Webb et al. 2000).

### *1.5.2 Overriding factors*

The practices of a farmer are not only significant to GHG outputs, but they are the factors with which they have the most immediate control over. These practices interact and differ in their effect depending on other variables, such as NIs reacting differently to different environments (Li et al., 2020; Oertel et al., 2017).

As another example, the type of fertilizer applied can significantly influence emissions, but this can be overridden by the soil type, with certain fertilizers being more suited to certain soils (Senbayram et al., 2019). Changing to a Nitrate fertilizer and increasing the Nitrate content of the soil can have more effect on emissions than attempting to change the physical soil characteristics, such as pH (Senbayram et al., 2019).

Previous studies have suggested that minimum tillage reduces carbon dioxide respiration whilst increasing carbon storage in soil (Thomson et al., 2012; Taft et al., 2018.) However, on soils with an already high quantity of organic matter the difference made is negligible (Taft et al., 2018). Kertesz and Madarasaz (2014) have also found that the effect of reducing tillage varies between countries and regions. A further study, looking specifically at tillage systems, found that biological factors can override any practice changes, with soil composition and microbial activity varying hugely amongst different areas and across different seasons (Hungria et al., 2009). Therefore, calling for minimum or no-tillage systems as a blanket policy for reducing GHG emissions and encourage carbon storage, may be ineffective for some farmers and serve only to reduce crop output, decreasing financial stability.

### *1.5.3 Vegetation*

Whilst the actions on a farm clearly influence the output of GHGs, the choice of crop also has an impact. The choice of plant species is another input that potentially affects GHG output, root respiration being a driver of emissions (Oertel et al., 2016). Different plants have different growing requirements and will have different demands from soil. One study looking into nitrogen losses noted that they differed significantly from crop to crop, with higher losses for sugar beet when compared with winter wheat (Webb et al., 2000). This variation extends to the activities taking place on farms. Crop choice determines the time of year that activities need to take place, thus influencing the GHG output (Taft et al., 2018; Hungria et al., 2009).

Horrocks et al. (2014) noted that vegetation type and quantity had an influence on soil temperature, a factor already established as having some effect on emissions, particularly carbon dioxide respiration. It was noted that crop residue was a particular influence on soil temperature, aligning with other findings (Horrocks et al., 2014; Dawar et al. 2020). This study, which examined the costs and benefits of extensification, concluded that there is limited knowledge about vegetations' impacts on GHG emissions and of the general outcomes of extensification (Horrocks et al., 2014).

Sanz-Cobena et al. (2014) found that, within the Mediterranean region, increasing crop residue also increases emissions. They also noted a difference in emissions between crops leading to the conclusion that crop choice is considered a factor influencing GHG output, or even as a mitigation method. A local study, conducted by Jeswani et al (2018), researching into the lifecycles of GHG emissions on organic farms in the UK, found that crop rotations and crop type varied dramatically. Their findings revealed that crops such as beans had twice or sometimes three times the output of emissions as cereal crops. Whilst the study was confined to only a few crops and concentrated on livestock, it points to crop choice and the vegetation being considered as significant factors.

Roots from crops have an important impact on the emissions produced by land (Norberg et al., 2016). For example, a meta-analysis of background nitrous oxide emissions found that vegetable crops have higher output than others, such as cereals with larger root structure or pasture with less soil disruption (Dong-Gill et al., 2013). In the context of trees, root depth is linked to higher carbon storage, but it is difficult to measure the significance at levels lower than 20cm, where over a third of soil carbon is stored (Upson and Burgess, 2013; Oertel et al., 2016; Pries et al., 2018). The knowledge gap within this area of soil impacts our understanding of root respiration and GHG emissions from cereal crops. Cereal roots can extend as far as 2.5 metres in depth, reaching below the 30cm topsoil layer (Thorup-Kristensen et al., 2009; Upson and Burgess., 2013).

Overall, a farmer's crop choices and rotations can impact the sustainability and GHG output of their land. Premrov et al. (2010) highlighted the importance of this with the suggestion of the need for crop specific emissions factors.

### *1.5.4 Nitrification inhibitors*

A method endorsed by the International Panel on Climate Change (IPCC) and several studies is the use of Nitrification Inhibitors (NIs) (Cowan et al., 2020; Roder et al., 2013; Abalos et al., 2016). Roder et al. estimated that the potential for reducing GHG emissions could be as much as 20%, when using NIs (Roder et al., 2013).

NI's slow the first stage of Nitrification; the change from ammonia to nitrite. They achieve this by inhibiting the activity of soil bacteria that would be producing both the nitrites and nitrous oxide (Frye, 1981). Slowing this process down means more available oxygen for nitrifying bacteria, leading to more Nitrite being produced and less nitrous oxide.

NI's are susceptible to many of the same influences as soils in general (Oertel et al., 2017). Bell et al. (2015) found that soil and weather conditions not only affected general emissions, but also the efficacy of NIs. Under the circumstances of the experiment, the use of a NI was found to be overall effective (Bell et al. 2015).

Dawar et al. (2021) found a direct link between NI efficacy and the conditions of the soil - specifically, temperature was found to be significant. NIs ability to perform is also affected by external environmental factors, such as rainfall (Li et al. 2020; Abalos et al. 2016). Rainfall is also major factor in this, along with the N2O emissions and how effective fertilisers are generally (Abalos et al., 2016). In the UK rainfall is found to be a more influential factor whereas in other countries heat can be more significant, such as in Pakistan (Li et al., 2020).

NI's are a useful tool in making fertiliser usage more efficient, controlling the soil bacteria by which nitrous oxide is produced. They are affected by the same factors that change general GHG emissions, but are considered effective nonetheless (Roder et al., 2013; Cowan et al., 2020).

*1.5.5 Systems interaction*

The factors influencing micro-bacteria are not acting in isolation. They interact and overlap as part of a wider ecosystem. The processes that GHGs are involved with also overlap, influencing the outcome for each other (Chadwick et al. 2011).

One example of two systems influencing each other are the carbon and nitrogen cycles. Oertel et al. (2016) concluded that soil carbon/nitrogen ratios are very important and influential over GHG emissions from soil. Senbayram et al. (2016) investigated the long-term effects of liming on GHG output, finding that raising the pH, to make soils less acidic reduced nitrous oxide emissions. However, it also concluded that it was only effective if other factors were first addressed, specifically SOC content within the soil (Senbayram et al., 2016). Roche et al. (2016) also observed that nitrous oxide emissions are lower from low SOC soils. N2O is released when microbial activity is high and oxygen access is limited (Oertel et al. 2016; Webb et al. 2014). SOC increases microbial biomass (Prommer, 2019).

For carbon dioxide emissions, Gao et al. (2020) observed an example of this in the close relationship between the carbon and nitrogen cycles, showcasing a clear influence. Carbon dioxide is emitted at higher rates from soils with consistently low N content (Gao et al. 2020).

Webb et al. (2014) observed that denitrifying microbiota are inhibited by lack of Soil carbon, slowing down the process of denitrification. This was seen to be only significant on coarse/sandier soil types, with clay soils not having this effect (Webb et al. 2014). This observation is consistent with the findings of Taft et al. (2018). It has noted that not enough is understood about the interactions between soil nitrogen and carbon dioxide output, with no consistent relationship between application of nitrogen fertilizer (Gao et al. 2020). Butterbach-Bahl et al. (2013) also concluded that there is a need for further research within this area.

Despite this, Meijide et al. (2010) did observe a relationship between nitrogen fertilizer and methane output. They found a flux of methane following the application. This is due to a low metabolism during the process of Nitrification, where methane oxidation and breakdown is halted following nitrogen fertilizer being spread (Meijide at al. 2010). This occurs because of the demand for oxygen in the Nitrification process (Butterbach-Bahl et al.; 2013; Meijide at al. 2010).

For nitrous oxide outputs, the efficiency of nitrification is dependent on the oxygen availability and the microbial activity rate (Oertel et al., 2016). Higher rates of oxygen use, or limited oxygen availability mean less efficiency and more nitrous oxide production (Taft et al., 2018; Krol et al., 2016). However, for the process of denitrification less oxygen means less nitrous oxide produced. In this instance denitrification favours atmospheric nitrogen, continuing the nitrogen cycle (Martins, 2005).

Environmental systems are mostly viewed individually, ignoring the inherent interaction (Smith et al. 2013). In the case of soil and arable agriculture the interaction of aspects such as the carbon and nitrogen cycle or the different reactions to mitigation techniques, demand a holistic approach to their monitoring and management (Chadwick et al. 2011). This is on top of the overlapping nature of other factors discussed like soil moisture and temperature (Shang et al., 2020; Krol et al., 2016) or climate and region in general (Hungria et al., 2009), which are complex systems within themselves.

## 1.6 Results and implications

GHG emissions from arable agriculture revolve around the soil usage (Oertel et al. 2016). They are affected by external factors (rainfall, temperature, and climate) (Krol et al., 2016; Clarke and Fraser, 2004; Hungria et al., 2009) and internal factors (soil type, moisture, and Ph) (Krol et al., 2016; Taft et al., 2018; Thomson et al. 2012). These in turn are influenced by the choices a land-user makes, i.e., tillage, crop-choice, fertilizer (Oertel et al., 2016; Webb et al., 2000; Sanchez-Martin et al., 2010). Some of these factors are within the direct control of the land-user and others are not.

From a climatic perspective, soil temperature is an influential factor on GHG output, but its influence is often overridden by soil moisture or rainfall. Temperature is also something a grower has limited control over, with its seasonal nature. Moisture and rainfall both affect the respiration rate, changing the emissions of all three gases. Both rainfall and soil moisture are tied to regional factors with limited controllability, such as the weather, climate, and soil type.

As indicated previously, seasonality is an influential factor. Seasonally driven changes in temperature or soil moisture influence microbial life and emissions (Hungria et al., 2009; Oertel et al., 2016). This is especially relevant as the continued emissions of GHGs will lead to the dramatic changing of these seasons, making them more volatile (Kertesz and Madarasaz., 2014).

### *1.6.1 Applying context*

The UK has a varied landscape with a multitude of micro-climates and physical conditions (Defra 2021). Factors that affect GHG emissions split the country into different character regions already, with these characters affecting productivity and financial decisions. This impacts food production and crops choices, even between adjacent areas. For example, the East Midlands and East of England have different major crops, with the former favouring Vegetables and Brassicas (e.g. Oilseed Rape) whilst the latter area grows more cereals and tuberous plants (e.g. potatoes and sugar beet) (Defra, 2021). Any analysis must consider the regional variation, such as rainfall and landscape differences.

If you compare the landscape of areas like East Anglia with other parts of the country, you get more contrasts. East Anglian soils tend to be high in silt and clay, with depleting peat and chalk deposits (Pritchard et al. 2014). On the opposite side of England in Cornwall, the soils are most commonly sandy loam with high acidity (Cornwall Council, 2020). Because of the impact of soil type (Krol et al. 2016) and soil acidity (Thomson et al. 2012), this implies that the GHG emissions will differ between the two areas before accounting for management techniques.

The Met Office (2021a) definition of the Midlands experience rainfall of around 800mm per year, despite being directly adjacent to East England with less than 700mm per year. From the perspective of temperature, the Midlands have an annual average temperature of between 8 and 10 degrees Celsius (Met Office, 2021a). The East of England has less variation and a slightly higher average of between 9.5 and 10.5 degrees Celsius (Met Office, 2021b). These differences will again affect the GHG output of the regions, giving them different results despite the adjacent location. Yet using most current models, the differences between the emissions are unlikely to be captured (Terrer et al. 2021).

The factors known to influence GHG emissions vary across the UK. This indicates that a farms location will influence its initial GHG output along with the activities being performed. Policy aimed at encouraging GHG reduction must be flexible enough to reflect the variety of scenarios across the UK. Likewise, any attempt to predict and model the GHG emissions should reflect the previous factors.

### *1.6.2 Knowledge gaps*

Concerning accuracy, any model or coefficient that seeks to estimate GHG outputs must have considered the factors outlined within this literature review to give a significant level of accuracy. Emissions factor recommendations vary from the initial IPCC estimate of 1% of nitrogen applied (Penman et al., 2017), to 0.6% in wetter climates in a revised method (IPCC, 2019). Other studies have found both to be inaccurate, with the correct assumptions being as high as 1.83% (Zhou et al. 2017; Velthof et al. 2003).

There are several areas highlighted through this review that point to the need for further research to close knowledge gaps. For example, more effort needs to be put towards understanding of the true impact of SOC and N content's influence on microbial activity, with regards to quantifying impact on GHGs (Gao et al., 2020; Butterbach-Bahl et al. 2013).

Currently there is only a limited understanding of the interaction between plants, GHG emissions and specifically the carbon cycle (Horrocks et al., 2014). Terrer et al. (2021) pointed to underestimation in literature of plant influence in areas like grassland, but an overestimation in others, such as forests. When put under the predicted conditions of the future climate it was found that carbon storage unexpectedly increased by 8% on grassland soils but saw limited to no increase within forests (Terrer et al. 2021). This was not replicated by any current ecosystem model, indicating that current storage projections are not accurate.

### *1.6.3 Conclusion*

The purpose of this review has been to outline the nature of GHG emissions from arable agriculture. It has highlighted the central role of soil microbial life and the influence growers can have over its activity. Farmer's activities have significant influence over arable GHG emissions, especially in the forms of fertilizer usage and tillage. Simultaneously, the influence uncontrollable factors have over GHG emissions is also clear, in examples such as rainfall and temperature. There are limitations to the knowledge available, especially when it comes to predicting emissions.

With the goal of Net Zero, reducing GHG emissions is a necessary step in making agriculture's relationship with the environment sustainable. Historically farms have only been used to produce profits, but this is changing (Glendining et al., 2009). For the sustainability of the industry, farmers must adapt to the environmental issues of the 21$^{st}$ century. Farming with the environment in mind is beneficial to both the external and internal ecosystems involved on a farm (Kassam and Brammer, 2013). It not only benefits the local ecosystem, but also long-term production. This also protects the public stake in land, and the production potential for the land, meaning that the grower can stay in business for longer.

Assessing the GHG outputs of farming and food production is necessary for the sustainability of the agricultural industry. As illustrated by the gaps in knowledge and complicated inputs needed, it is also a difficult task to perform. Whilst it is always going to be more accurate to take direct measurements, this is costly and laborious. Farmers are more likely to make changes in the form of reduction or optimisation, rather than spending money on changes or expensive measurement methods (Feliciano et al. 2017). Innovations must be easily accessible and usable if they are to be effective.

Overall, more research is needed regarding the measurement of GHGs and the impact that practices and farm characteristics have over GHG output. The research that this review precedes attempts to address some of the issues presented here. The Farm Business Survey (FBS) documents the activities and characteristics of farms across the United Kingdom. Combining this information with the Sustainable Intensification research Platform's (SIP) greenhouse gas calculators with allow for this to take place (benchmarkmyfarm.co.uk, 2021). Aspects such as the choices made for inputs, technology and land use can be analysed for trends. Local characteristics, such as general location, topography and the areas land grading can also be used to observe the potential influence of climate and soil attributes. Finally, the overall efficacy of the Carbon calculator can be observed, as to whether it captures the variation in GHG emissions outlined throughout this literature review.

## 2.0 Sustainable intensification data analysis

### 2.1 Introduction

As illustrated by the previous review, reducing GHG emissions is an important issue that the UK agricultural industry is attempting to address (DEFRA, 2019; Glendining et al., 2009). To this end, farmers will need to rely on carbon measurements to gauge their business output and make positive changes via GHG reductions. This project analysed one such carbon accounting method, investigating its practical application at farm business level.

Decreasing the quantity of GHG's is essential to the sustainability of the agricultural industry and the wellbeing of the planet (Kertesz and Madarasaz., 2014). But with agriculture it comes with the risk of compromising food security. The concept of sustainable intensification aims to combat this, using fewer resources and creating lower negative externalities, whilst maintaining or improving food security. Therefore, this project also investigated the GHG output data alongside the food output data, in the forms of yield and financial output.

### 2.2 Aim and Objectives

The aim of this research was to observe the relationship between UK cereal farm characteristics and practices, comparing the relationship with its outputs. Simultaneously, the question asked is whether these observed relationships can be useful and to whom. These aims are sourced from the preceding review, which found that the climate, farm characteristics and the productive choices made by farm managers all impact GHG emissions. How well these are represented in the results will be discussed.

The outputs represent the consequences of farmers actions, being both positive and negative towards the environment and productivity. Outputs and therefore dependent variables included yields and estimated emissions. The agricultural production inputs, landscape, demographics of farmers and decisions made by farmers were included as independent variables to determine their influence on the physical (including GHG's) and financial outputs of the farm.

This research utilises the FBS data on farm business practices. The SIP provides coefficients to convert activities recorded in the FBS into carbon equivalent data, estimating the quantity of GHGs produced as equivalent to carbon dioxides impact. The project examined outputs from several different levels: from a farm level, from a per hectare level and from a per tonne level. This can address the impact the level of measurement (the functional unit) can have on results.

The three areas of important influence identified were the location of a farm from its climate perspective (weather, temperature, rainfall), its location from a physical perspective (soil type, Ph, topography), and finally the impact of the farmers decisions (inputs, techniques). This leads to the following research questions:

Can the environmental impact associated with location be observed using FBS data on activities? This question was addressed using the Joint character area (JCA) codes from the FBS. The location of a farm dictates its climatic conditions, found to be significant in the review.

Can the impact of the soil properties be observed using FBS data? This question was addressed using the land grade data associated with the JCA codes and the Centre for Ecology and Hydrology (CEH) codes, also from the FBS. Soil properties influence the productive choices made by a farmer and change the microbial environment of the soil, both of which were found to significantly influence GHG emissions in other literature.

Can the impact of decisions made by farmers be observed using the FBS dataset? This question was addressed using the data on inputs and surveys for activities, from the FBS. As previously stated, a farmers actions impact the conditions of the soil, changing the activities of soil microbes and consequently the rates of GHG emissions. This question is also central to whether this particular Carbon equivalency coefficient has use towards informing farmers in their production choices, besides as a broad-spectrum benchmarking tool.

## 2.3 Method

The data set used contains information from 336 cereal farms. A cereal farm classification is given when cereals comprise at least 66% of farm output. (Number of farm) farms that produced no cereal in this year were excluded from the dataset, even if classed as cereal farms. Farms that came under the classification of part-time production were also removed. Finally, Welsh farms, under the country classification 421, were removed, due to lack of data and survey elements not being applicable. The data concerning the outputs of cereal farms are available from the 2017 FBS in the case of yields and financial output or derived using the SIP multipliers combined with data from the 2017 FBS, for greenhouse gas (GHG) emissions. These multipliers were derived from the IPCC's guidelines on land management (de Klein et al., 2006). The year 2017 was chosen as this is the final year that the SIP carbon equivalent multipliers were known to have been updated (eip-agri, 2017).

Linear regression analyses were performed to observe the association between agricultural practices and the various outputs of the farms. This model is where multiple independent variables ($x$) have relationships with a dependant variable ($y$), that is a straight line (Hayes, 2021). This linear regression model is given by

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon$$

where the intercept β0 (constant) and the slope of β1/β2/βn are unknown constants of the independent variables and ε is a random error (Hayes, 2021; Ibrahim et al. 2012). β0 and β1/β2/βn are then estimated with the data provided (Hayes, 2021). ε is assumed to have a mean of zero and unknown variance (Hayes, 2021). This form of regression is also called the least squares regression equation and selects the smallest sum of residual squares to find the best fitting line, which is what is presented (Ibrahim et al. 2012). This is where

$$\sum_{i=l}^{n}(y_i - \hat{y}_i)^2$$

represents the minimum sum of residual squares, as calculated by the statistical program used (Ibrahim et al. 2012; Hayes, 2021).

These analyses were performed using the sixteenth edition of the statistical package STATA with a maximal model utilising the independent variables. Twenty-five independent variables were tested against 4 dependent variables. Independent variables were sorted into three groups: Agricultural inputs and activities, decisions and demographics, and finally the farm characteristics. The four dependent variables each tested an output of the farm; physical (yields; cereals tonnes produced), financial (earnings from yields of cereal), nitrogen-based emissions (sourced from fertiliser use in kilograms and using the SIP carbon dioxide multiplier), and total direct emissions (including fertiliser/nitrogen emissions but also the other carbon emissions from Petrol, Gas and Diesel use, all presented in litres with the respective SIP carbon dioxide multiplier). When utilising the per hectare and per tonne models, the variables are divided by the respective amount, either the hectares of cereal land or the tonnes of cereal produced.

Models were created and reduced to find the minimal adequate model, as the significance of each variable became apparent. Significance is defined as a probability value of less than 0.05 or 95%. This was performed in three stages. The three stages allow for the impact of each category of independent variable to be observed, adding further context to their influence or lack thereof.

When variables cannot be considered independent and represent a high level of multi-collinearity, they were removed or inserted separately. For example, fertiliser usage is used to calculate the nitrogen-based emissions, and so is removed as an independent variable in the models concerning nitrogen-based emissions. Similarly, fossil fuel usage (diesel, petrol, gas) is used for the calculation carbon emissions, so each is eliminated as an independent variable from the total carbon equivalent emissions models. The final example of this is the use of the FBS farm size category, which will not be used alongside a farms land area. These would be a form of data-based multi-collinearity, where the new dependant variable has been created from the other potential variables (Daoud, 2017).

## 2.4 Variable description

The following section describes the variables used to make the models. It is split into four sections divided into the categories previously outlined: the dependant variables, and the three categories of independent variables. All are sourced from the 2017 FBS.

### *2.4.1 Dependant Variables*

The first two dependant variables representing production metrics are the yield and the financial outputs produced by each farm. Both are measures of farm productivity. Physical crop yield is a contributor to food security yields and are given in metric tonnes. Financial Output is the revenue achieved from the sale of cereals and is given in the currency of Pounds sterling (£).

The second two dependant variables representing sustainability metrics are the emissions sourced from nitrogen fertilisers and the total direct emissions generated by the farm. Both are measures of the impact of farm practices and the farms sustainability.

Nitrogen-based emissions were calculated from total N fertilizer applied (Kg) multiplied by the coefficient (given as 0.0093 from the Country Land and business owners Association Carbon Accounting from Land Managements carbon equivalency calculator) to produce a Carbon Equivalent figure (the equivalent tonnage of CO2 produced per farm).

The dataset used for this study has further coefficients concerning carbon equivalent emissions. These are sourced using the farms fossil fuel usage. The coefficients used for these estimates are sourced from the Department of Energy and Climate Change (DECC). They utilize the quantity of the fuels used, in litres, before converting these into CO2 tonne equivalents (Diesel in litres multiplied by 0.003, petrol in litres multiplied by 0.0023, and gas in kilowatt-hours multiplied by 0.00025). Included in this calculation is the previously outlined Nitrogen sourced emissions, give the total direct emissions from each farm.

### *2.4.2 Table 1. Dependant variables*

| Dependant Variables: | Unit | Mean | Std. Dev. | Range |
|---|---|---|---|---|
| Cereal Yield | metric tonne | 1140.00 | 1274.00 | 15726.20 |
| Cereal Output | £ or Pounds sterling | 302440.04 | 312046.56 | 3221364.00 |
| Nitrogen-based emissions | Equivalence to tonne of Carbon | 345.00 | 372.60 | 3647.55 |
| Direct emissions | Equivalence to tonne of Carbon | 417.00 | 436.19 | 4314.97 |

*2.4.3 Agricultural inputs and activities*

Activities associated with emissions were tested to observe their impact on yields and other outputs. Key inputs may be influential on yields but also be on other unwanted outputs. The three primary inputs of seed, fertiliser, and Crop Protection Products (CPP) are all included. Land area is also included in this category, due to the potential influence it will have over total yields and outputs.

Areas such as fuel expense not only represents a direct emission of carbon dioxide, but also indicates farm vehicle use. Because of this, they can be used as a marker for field activities, including tillage. This data covers amount spent of diesel, petrol, gas, electricity, and heating.

Other machinery costs and contracting costs represent usage not included in the diesel expenditure. For example, contractors represent emissions and tillage, but will pay for their own fuel (assumed to be included in the contractor cost as one of their expenses, but not directly from the farm).

Although payments for environmental schemes can be viewed as an output, it is a representation of the value of the activities performed. This is as opposed to the market cost of the activity, which does not consider the intangible advantage created. Because of this, the environmental scheme payments will be used as an independent variable.

To maintain consistency, these measurements are all costs, so the unit is GBP£ spent/received on/for the product or activity. The exception to this is the area used for cereals, which is presented in hectares.

*2.4.4 Table 2: Agricultural inputs and activities*

| Independent Variable: | Definition | Unit: | Mean: | Range: | Std. Dev: |
|---|---|---|---|---|---|
| Cereals Area | Farm area of cereals planted | Hectares | 143.14 | 1417.68 | 136.32 |
| Fertiliser | Quantity spent on Fertilizer | GBP£ | 32647.71 | 329402 | 34045.23 |
| Seed | Quantity spent on Seed | GBP£ | 16642.23 | 204810 | 20169.59 |
| CPP (Crop protection products) | Quantity spent on Crop protection products | GBP£ | 38731.60 | 473573 | 45022.33 |
| Machinery | Quantity spent on Machinery | GBP£ | 57884.51 | 338167 | 55548.10 |
| Contract | Quantity spent on Contract work | GBP£ | 21508.34 | 320804 | 37045.35 |
| Diesel | Quantity spent on Diesel | GBP£ | 11256.99 | 111129 | 14383.84 |
| Petrol | Quantity spent on Petrol | GBP£ | 2953.65 | 82954 | 6377.43 |
| Gas | Quantity spent on Gas | GBP£ | 88.37 | 5609 | 564.67 |
| Electricity | Quantity spent on Electricity | GBP£ | 3264.62 | 41186 | 4615.88 |

| | | | | | |
|---|---|---|---|---|---|
| Heating | Quantity spent on Heating | GBP£ | 2033.58 | 22338 | 3442.36 |
| Environmental payments | Quantity received for Environmental services | GBP£ | 6412.23 | 116242 | 13271.90 |

*2.4.5 Demographics and decisions*

The FBS contains information about the demographics of farm managers and specific management decisions that they make. The influence of these variables were observed on the dependant variables.

Specific decisions were tested for their influence over outputs. For example, the relationship between decision to be a member of the environmental organisation 'LEAF' and environmental consequences, could showcase whether membership does or does not encourage the sustainable practices that the organisation pushes (LEAF, 2021). Alternatively, precision agriculture and nutrient software usage potentially increase efficiency and are presented as options to improve agricultural sustainability (Balafoutis et. al, 2017).

It is worth noting that the survey data is discrete, categorical, usually being distributed between three-four answers (yes/no/Partial/not applicable answers). The categories that do not present this way use numbers representing scales given in the FBS and listed below. Due to the categorical nature of these inputs, dummy variables were created for each outcome.

*2.4.6 Table 3: Decisions and Demographics*

| Variable | Description | No. of Levels | Definition | Occurrence | Mean | Mode | Median |
|---|---|---|---|---|---|---|---|
| Gender | Gender of cereal farmer | 2 (1-2) | 1/Male (base), 2/Female | 1/323, 2/13 | 1.04 | 1/Male | 1/Male |
| Age band | Age group of cereal farmer | 6 (1-6) | 1/<35 (base), 2/35-<45, 3/45-<55, 4/55-<65, 5/65-<75, 6/75+ | 1/9, 2/33, 3/74, 4/100, 5/92, 6/28 | 3.94 | 4/55-<65 | 4/55-<65 |
| Education level | Highest level of education of farm manager | 8 (0-6, 9) | 0/School Only (base), 1/GCSE, 2/A level, 3/Diploma, | 0/33, 1/34, 2/18, 3/149, 4/83, | 2.82 | 3/Diploma | 3/Diploma |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | 4/Degree, 5/Postgrad, 6/Apprenticeship, 9/Other | 5/18, 6/0, 9/1 | | | |
| Precision Farming | Whether the cereal farm makes use of precision farming methods | 4 (1-4) | 1/No (base), 2/Yes, 3/Partial, 4/N/A | 1/159, 2/149, 3/26, 4/2 | 1.62 | 1/No | 2/Yes |
| Use of Nutrient software | Whether the cereal farm uses soil nutrient software | 4 (1-4) | 1/No (base), 2/Yes, 3/Partial, 4/N/A | 1/160, 2/174, 3/2, 4/0 | 1.53 | 2/Yes | 2/Yes |
| Use of Green manures | Whether a farm uses green manures | 4 (1-4) | 1/No (base), 2/Yes, 3/Partial, 4/N/A | 1/268, 2/56, 3/12, 4/0 | 1.24 | 1/No | 1/No |
| Adjusted fertiliser | Whether a farm adjusts fertilizer rates for manures | 4 (1-4) | 1/No, 2/Yes, 3/Partial, 4/N/A | 1/35, 2/80, 3/221, 4/0 | 2.55 | 3/Partial | 3/Partial |
| Source of Knowledge | Source of advice for crop nutrient planning | 5 (1-5) | 1/Own advice (no FACTS qualification) (base), 2/Own advice (FACTS qualified), 3/Independent FACTS advisor, 4/Fertilizer representative, 5/N/A | 1/63, 2/30, 3/159, 4/84, 5/0 | 2.79 | 3/Independent FACTS advisor | 3/Independent FACTS advisor |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Farm assurance membership | Whether the farm has members hip with a farm assurance | 2 (1-2) | 1/Not a member (base), 2/Member | 1/35, 2/301 | 1.9 | 2/Member | 2/Member |
| LEAF membership | Whether a farm has members hip with the organisati on, 'LEAF'. | 2 (1-2) | 1/Not a member (base), 2/Member | 1/300, 2/36 | 1.11 | 1/Not a member | 1/Not a member |

*2.4.7 Farm characteristics data*

The final category of independent variables aims to look at the physical and environmental impacts on farms, based upon location and physical characteristics. Because of the overlapping nature of these variables, they are added to the models separately.

The JCA codes are assigned to each farm and group them into areas with similar conditions. These data were used to observe the impact of location and the characteristics associated with each location on emissions and outputs. JCA code 46, the fens, was used as a base, because of the funding provided by East Anglian trusts, a suitable quantity of cereal farms in this survey found in the area, and the general interest in carbon emissions of the area.

The CEH gives farms a code similar to the JCA but sorting each farm into a category describing the vegetation and topography of its situation. These data were used to provide an alternative indication of the impact of location on emissions and outputs. CEH code 3, described as ‘Flat arable land, mainly cereals, little native vegetation’, was used as a base for these categories.

An area that deserves exploration is the financial capability and general vulnerability of farms in relation to eco-system services, such as reducing emissions. One marker of wealth or access to resources is a farms size. Because of this, comparing emissions to land area farmed could produce interesting results. This would further the idea of farm capability; are larger or more wealthy farms better able to reduce emissions. Farms are given a classification of small, medium, and large, but there is also information on the Hectares used for cereals and the total farm area.

This dataset was derived using data previously collected on the percentage of each Agricultural Land Grade in each of the JCAs. This percentage has then been applied to the area of the farm used for cereals, indicating a farm-wide land quality figure. These data were used to give detail to the JCA codes about the characteristics present in each area. The predicted quantity of grade 1 land was used as a base figure for the other categories.

*2.4.8 Table 4: Farms characteristics data*

| Variable | Definition | Occurrence and Levels | Occurrence | Mean | Median | Mode | Range |
|---|---|---|---|---|---|---|---|
| Joint Character Area Code | Area farm is located in, sorted into shared characteristics | 92/152 | N/A | N/A | N/A | N/A | N/A |
| Centre for Ecology and Hydrology Land Classification Codes | Description of landscape and land usage | 20/32 | N/A | N/A | N/A | N/A | N/A |
| Farm Size | The FBS classification of farm size (1/Small, 2/Medium, 3/Large). | N/A | 1/46, 2/133, 3/157 | 2.33 | Medium/ 2 | Large/ 3 | N/A |

| Variable | Definition | Unit: | Mean: | Std: Dev: | Range: |
|---|---|---|---|---|---|
| Grade 1 ha (base) | Estimated quantity of Grade 1 (highest quality) land on farm (Used as Base for other grades) | Hectares | 12.92 | 31.53 | 120.28 |
| Grade 2 ha | Estimated quantity of Grade 2 land on farm | Hectares | 66.22 | 50.99 | 171.18 |
| Grade 3 ha | Estimated quantity of Grade 3 (most common quality) land on farm | Hectares | 160.22 | 64.13 | 262.85 |
| Grade 4 ha | Estimated Quantity of Grade 4 land on farm | Hectares | 24.65 | 28.89 | 150.36 |
| Grade 5 ha | Estimated quantity of Grade 5 (lowest quality) land on farm | Hectares | 2.49 | 9.91 | 115.27 |

## 3.0 Results

### 3.1 Results Summary

The final models (with the highest R-Squared value) created via this process led to the following equations:

#### 3.1.1 Final farm level regression equations:

Regression model 1: Yield farm total

$$CerT = \beta_0 + \beta_1 CerHa + \beta_2 Seed£ + \beta_3 Fer£ + \beta_4 CPP£ + \beta_5 Mach£ + \beta_6 Cont£ + \beta_7 Die£ + \beta_8 Elec£ + \beta_9 Heat£ + \varepsilon$$

Regression model 3: Financial Output farm total

$$Cer£ = \beta_0 + \beta_1 CerHa + \beta_2 Fer£ + \beta_3 CPP£ + \beta_4 Env£ + \beta_5 Env£ + \beta_6 FrmGr2 + \beta_7 FrmGr3 + \beta_8 FrmGr3 + \beta_9 FrmGr4 + \beta_{10} FrmGr5 + \varepsilon$$

Regression model 5: Nitrogen-based emissions farm total

$$FerKg * CO_2eq = \beta_0 + \beta_1 CerHa + \beta_2 Seed£ + \beta_3 CPP£ + \beta_4 Gas£ + \beta_5 FrmGr2 + \beta_6 FrmGr3 + \beta_7 FrmGr3 + \beta_8 FrmGr4 + \beta_9 FrmGr5 + \varepsilon$$

Regression model 8: Direct emissions farm total

$$PetL * CO_2\text{eq} + \text{GaskWh} * CO_2\text{eq} + \text{DiesL} * CO_2\text{eq} + \text{FerKg} * CO_2\text{eq} = \beta_0 + \beta_1 CerHa + \beta_2 Seed£ + \beta_3 CPP£ + \beta_4 Mach£ + \varepsilon$$

#### 3.1.2 Final per Ha regression equations:

Regression model 2: Yield per hectare

$$\frac{CerT}{CerHa} = \beta_0 + \beta_1 \frac{Seed£}{CerHa} + \beta_2 \frac{Fer£}{CerHa} + \beta_3 \frac{CPP£}{CerHa} + \beta_4 \frac{Prec2}{CerHa} + \beta_5 \frac{Prec3}{CerHa} + \beta_6 \frac{Prec4}{CerHa} + \beta_7 \frac{FrmS2}{CerHa} + \beta_8 \frac{FrmS3}{CerHa} + \varepsilon$$

Regression model 3: Financial output per hectare

$$\frac{Cer£}{CerHa} = \beta_0 + \beta_1 \frac{Seed£}{CerHa} + \beta_2 \frac{Fer£}{CerHa} + \beta_3 \frac{CPP£}{CerHa} + \beta_4 \frac{Prec2}{CerHa} + \beta_5 \frac{Prec3}{CerHa} + \beta_6 \frac{Prec4}{CerHa} + \beta_7 \frac{GreM2}{CerHa} + \beta_8 \frac{GreM3}{CerHa} + \beta_9 \frac{FrmS2}{CerHa} + \beta_{10} \frac{FrmS3}{CerHa} + \varepsilon$$

Regression model 6: Nitrogen-based emissions per hectare

$$\frac{FerKg * CO_2eq}{CerHa} = \beta_0 + \beta_1\frac{CPP£}{CerHa} + \beta_2\frac{Mach£}{CerHa} + \beta_3\frac{Cont£}{CerHa} + \beta_4\frac{GreM2}{CerHa} + \beta_5\frac{GreM3}{CerHa} + \beta_6\frac{Sour2}{CerHa} + \beta_7\frac{Sour3}{CerHa} + \beta_8\frac{Sour4}{CerHa} + \beta_9\frac{LEAF}{CerHa} + \beta_{10}\frac{FrmGr2}{CerHa} + \beta_{11}\frac{FrmGr3}{CerHa} + \beta_{12}\frac{FrmGr4}{CerHa} + \beta_{13}\frac{FrmGr5}{CerHa} + \varepsilon$$

Regression model 9: Direct emissions per hectare

$$\frac{Petl * CO_2\mathrm{eq} + \mathrm{GaskWh} * CO_2\mathrm{eq} + \mathrm{DiesL} * CO_2\mathrm{eq} + FerKg * CO_2eq}{CerHa} = \beta_0 + \beta_1\frac{CPP£}{CerHa} + \beta_2\frac{Mach£}{CerHa} + \beta_3\frac{Cont£}{CerHa} + \beta_4\frac{Env£}{CerHa} + \beta_5\frac{Prec2}{CerHa} + \beta_6\frac{Prec3}{CerHa} + \beta_7\frac{Prec4}{CerHa} + \beta_8\frac{LEAF}{CerHa} + \beta_9\frac{FrmGr2}{CerHa} + \beta_{10}\frac{FrmGr3}{CerHa} + \beta_{11}\frac{FrmGr4}{CerHa} + \beta_{12}\frac{FrmGr5}{CerHa} + \varepsilon$$

## <u>3.1.3 Final per Tonne regression equations:</u>

Regression model 7: Nitrogen-based emissions per tonne

$$\frac{FerKg * CO_2eq}{CerT} = \beta_1\frac{CPP£}{CerT} + \beta_2\frac{Mach£}{CerT} + \beta_3\frac{GreM2}{CerT} + \beta_4\frac{GreM3}{CerT} + \beta_5\frac{Sour2}{CerT} + \beta_6\frac{Sour3}{CerT} + \beta_7\frac{Sour4}{CerT} + \beta_8\frac{LEAF}{CerT} + \beta_9\frac{FrmGr2}{CerT} + \beta_{10}\frac{FrmGr3}{CerT} + \beta_{11}\frac{FrmGr4}{CerT} + \beta_{12}\frac{FrmGr5}{CerT}\varepsilon$$

Regression model 10: Direct emissions

$$\frac{Petl * CO_2\mathrm{eq} + \mathrm{GaskWh} * CO_2\mathrm{eq} + \mathrm{DiesL} * CO_2\mathrm{eq} + FerKg * CO_2eq}{CerHa} = \beta_0 + \beta_1\frac{Seed£}{CerT} + \beta_2\frac{CPP£}{CerT} + \beta_3\frac{Mach£}{CerT} + \beta_4\frac{Cont£}{CerT} + \beta_5\frac{Env£}{CerT} + \beta_6\frac{Prec2}{CerT} + \beta_7\frac{Prec3}{CerT} + \beta_8\frac{Prec4}{CerT} + \beta_9\frac{LEAF}{CerT} + \beta_{10}\frac{GreM2}{CerT} + \beta_{11}\frac{GreM3}{CerT} + \varepsilon$$

*3.1.5 Table 5: Regression equation variable key*

| **Variable label** | **Variable definition** |
|---|---|
| CerT | Yield of cereals in tonnes |
| Cer£ | Financial output of cereals in £/GBP |
| FerKg | Nitrogen fertilizer used in KG |
| PetL | Petrol used in Litres |
| GaskWh | Gas used in kWh |
| DiesL | Diesel used in Litres |
| CO2eq | Relevant CO2 equivlant multiplier |
| | |
| CerHa | Land used for cereals in Hectares |
| Seed£ | Quantity spent on seed in £/GBP |
| Fer£ | Quantity spent on fertilizers in £/GBP |
| CPP£ | Quantity spent on CPP in £/GBP |
| Mach£ | Quantity spent on machinery in £/GBP |
| Cont£ | Quantity spent on contracting in £/GBP |
| Dies£ | Quantity spent on diesel in £/GBP |
| Pet£ | Quantity spent on petrol in £/GBP |
| Gas£ | Quantity spent on gas in £/GBP |
| Heat£ | Quantity spent on other heating in £/GBP |
| Elec£ | Quantity spent on electricity in £/GBP |
| Env£ | Quantity received from environmental services in £/GBP |
| Prec2,..,Prec4 | Level of precision farming implementation |
| GreM2,..,GreM3 | Level of Green Manure implementation |
| Sour2,..,Sour5 | Source of knowledge for crop nutrition |
| LEAF | Leaf membership |
| FrmS2, FrmS3 | Level of farm size |
| FrmG2,..,FrmG5 | The farms proportional land grade |

## 3.2 Regression Results: Production metrics

### 3.2.1 Yield

*Farm Level: Regression table 1*

For the initial farm level model including activities and inputs, the following variables were found to have significant positive association: cereals area (p<0.01, 6.166), fertiliser inputs (p<0.01, 0.00633), crop protection inputs (p<0.01, 0.00414), diesel (p<0.01, 0.00681) and electricity usage (p<0.05 0.00912). Seed costs (p<0.01, 0.00777), machinery costs (p<0.01, -0.00405), contract costs (p<0.05, -0.00109) and heating fuel costs (p<0.01, -0.0167) were found to have significant negative association. This model has an R-squared value of 0.96.

Neither demographic or decisions-based data nor farm characteristics data added anything significant to the model.

*Per Hectare: Regression table 2*

For the initial 'per Hectare' model including activities and inputs the following variables were found to have significant positive association: fertiliser inputs (p<0.01, 0.00422) and crop protection inputs (p<0.01, 0.00592). Seed costs (p<0.01, -0.00639) were found to have significant negative association. This model has an R-squared value of 0.303.

Adding in the demographics and decision-making data found that the use of precision agriculture (p<0.05, 0.0484) has significant positive association. This model has an R-squared value of 0.328.

Finally, adding in farm characteristics data showed that large farms have a positive significant association (p<0.05, 0.487) compared to those classified as medium or small. This model has an R-squared value of 0.336.

**Financial Output 3.2.2**

*Farm Level: Regression table 3*

For the initial farm level model including activities and inputs the following variables were found to have significant positive association: cereals area ($p<0.01$, 1567), fertiliser ($p<0.01$, 1.385) and crop protection ($p<0.01$, 1.492), and environmental payments ($p<0.05$, 0.692). Seed costs ($p<0.01$, -1.074) were found to have significant negative association. This model has an R-squared value of 0.952.

No demographic or decision-making data held any significance when added to this model.

Finally adding in farm characteristics data to the initial model found two categories of the farms land grade data, grade's 3 ($p<0.05$, -267.6) and 4 ($p<0.01$, -514.7) to be significant and have a negative association. Environmental payments became more significant with this inclusion ($p<0.01$, 0.838). This model has an R-squared value of 0.954.

*Per Hectare: Regression table 4*

For the initial 'per Hectare' model including activities and inputs the variables fertilizer ($p<0.01$, 1.280) and crop protection ($p<0.01$, 1.581) were found to have significant positive association. Seed costs ($p<0.01$, -1.573) were found to have significant negative association. This model has an R-squared value of 0.273.

Adding in the demographics and decision-making data found that the use of precision farming ($p<0.01$, 132.6) and of green manures ($p<0.05$, 138.6) has significant positive association. This model has an R-squared value of 0.314.

Finally, adding in farm characteristics data showed that large farms have a positive significant association ($p<0.01$, 167.4) compared to those classified as medium or small. Precision farming became less significant with this inclusion ($p<0.05$, 102.1). This model has an R-squared value of 0.325.

<u>Regression Results tables: Production metrics</u>
The results are presented below with the coefficient represented, the standard errors in parentheses, and the p value given an approximation through a scale of asterisk's (*** p<0.01, ** p<0.05). Variables with a p value of more than the required 0.05, but are a part of a categorical set, are presented in bold and underlined.

### 3.2.3 Yield

*Regression table 1:*

| VARIABLES | Farm level yields |
|---|---|
| Cereals area | 6.166*** |
| | (0.315) |
| Seed | 0.00777*** |
| | (0.00190) |
| Fertiliser | 0.00633*** |
| | (0.00133) |
| Crop Protection Products (CPP) | 0.00414*** |
| | (0.000986) |
| Machinery | -0.00405*** |
| | (0.000570) |
| Contract | -0.00109** |
| | (0.000533) |
| Diesel | 0.00681*** |
| | (0.00170) |
| Electricity | 0.00912** |
| | (0.00425) |
| Heating Fuel | -0.0167*** |
| | (0.00456) |
| Constant | -53.94** |
| | (22.96) |
| Observations | 336 |
| R-squared | 0.960 |

*Regression table 2:*

| VARIABLES | Model 1<br>Per ha Yields | Model 2<br>Per ha Yields | Model 3<br>Per ha Yields |
|---|---|---|---|
| Seed/ha | -0.00639*** | -0.00586*** | -0.00581*** |
| | (0.00177) | (0.00179) | (0.00178) |
| Fertiliser/ha | 0.00422*** | 0.00390*** | 0.00394*** |
| | (0.00102) | (0.00101) | (0.00101) |
| CPP/ha | 0.00592*** | 0.00546*** | 0.00514*** |
| | (0.000854) | (0.000863) | (0.000875) |
| Precision farming – Yes – 2 | | 0.484*** | 0.407** |
| | | (0.157) | (0.164) |
| Precision farming = Partial – 3 | | 0.304 | 0.247 |
| | | (0.287) | (0.288) |
| Precision farming – N/A - 4 | | -1.473 | -1.405 |
| | | (0.997) | (0.994) |
| Farm size – Medium - 2 | | | 0.373 |
| | | | (0.234) |
| Farm size – Large - 3 | | | 0.487** |
| | | | (0.241) |
| Constant | 5.955*** | 5.857*** | 5.591*** |
| | (0.248) | (0.249) | (0.292) |
| Observations | 336 | 336 | 336 |
| R-squared | 0.303 | 0.328 | 0.336 |

*Precision farming base: 1/does not use precision farming methods*

*Farm size base: 1/Small*

### 3.2.4 Financial Output

*Regression table 3:*

| VARIABLES | Model 1<br>Farm Level Financial Output | Model 3<br>Farm Level Financial Output |
|---|---|---|
| Cereals area | 1,567*** | 1,576*** |
| | (82.45) | (81.92) |
| Seed | -1.074** | -1.379*** |
| | (0.465) | (0.476) |
| Fertiliser | 1.385*** | 1.534*** |
| | (0.344) | (0.347) |
| Crop Protection Products (CPP) | 1.492*** | 1.433*** |
| | (0.257) | (0.257) |
| Environmental payments | 0.692** | 0.838*** |
| | (0.305) | (0.308) |
| Land Grade 2 | | -293.1 |
| | | (156.9) |
| Land Grade 3 | | -267.6** |
| | | (117.1) |
| Land Grade 4 | | -514.7*** |
| | | (178.2) |
| Land Grade 5 | | -419.9 |
| | | (406.5) |
| Constant | -11,498** | 64,860** |
| | (5,667) | (32,019) |
| Observations | 336 | 336 |
| R-squared | 0.952 | 0.954 |

*Land grade base: 1/quantity of land graded 1 on farm*

*Regression table 4:*

| VARIABLES | Model 1<br>Per ha Financial Output | Model 2<br>Per ha Financial Output | Model 3<br>Per ha Financial Output |
|---|---|---|---|
| Seed/ha | -1.573*** | -1.885*** | -1.847*** |
| | (0.534) | (0.558) | (0.555) |
| Fertiliser/ha | 1.280*** | 1.327*** | 1.324*** |
| | (0.308) | (0.306) | (0.305) |
| CPP/ha | 1.581*** | 1.561*** | 1.444*** |
| | (0.257) | (0.263) | (0.267) |
| Precision farming – Yes – 2 | | 132.6*** | 102.1** |
| | | (47.43) | (49.30) |
| Precision farming – Partial – 3 | | <u>24.87</u> | <u>2.403</u> |
| | | <u>(85.96)</u> | <u>(86.07)</u> |
| Precision farming – N/A – 4 | | <u>-80.76</u> | <u>-56.24</u> |
| | | <u>(299.6)</u> | <u>(298.3)</u> |
| Green manure usage – Yes – 2 | | 138.6** | 131.2** |
| | | (64.57) | (64.45) |
| Green manure usage – Partial - 3 | | <u>-225.0</u> | <u>-231.1</u> |
| | | <u>(119.9)</u> | <u>(119.3)</u> |
| Farm size – Medium – 2 | | | <u>101.0</u> |
| | | | <u>(70.13)</u> |
| Farm size – Large - 3 | | | 167.4** |
| | | | (72.19) |
| Constant | 1,537*** | 1,493*** | 1,418*** |
| | (74.79) | (75.42) | (87.67) |
| Observations | 336 | 336 | 336 |
| R-squared | 0.273 | 0.314 | 0.325 |

*Precision farming base: 1/does not use precision farming methods*

*Green manure base: 1/does not use green manures*

*Farm size base: 1/Small*

## 3.3 Results interpretation: Productivity metrics

### 3.3.1 Yield

For total yields at a farm level (Regression table 1) increasing the costs of inputs used (seed, fertiliser, CPP) also increases output. Similar to this, the more land a farm devotes to cereals the higher the total yields. Expenses on machinery and contracting negatively impact yields. The assumption could be made that this is representative of smaller farms who are more likely to contract out work and will have higher machinery costs when compared to their size and potential output. Heating fuel also had a negative impact which could be a result of the types of farms using such fuel for activities such as grain drying. For the yield per hectare (regression table 2), seed costs instead have a negative impact, but other inputs remain positive. This could be because at a farm level (regression table 1), more farmland devoted to the crop results in a higher yield, but also higher need for seed, whereas at the per hectare level (regression table 2) increasing seed application and expense on seeds is less efficient when it comes to yield (Cheema et al. 2013). At this level precision farming shows a positive impact on yields possibly due to the ability. This could be due to larger farms, with higher overall yield potential having the ability and less risk to implement novel techniques, like precision farming. Finally, the category of overall farm size shows that larger farms have a significantly higher yield per hectare.

### 3.3.2 Financial output

The total financial output (regression table 3) generally increased with the quantity of inputs (area of land, CPP, fertiliser). The exception for this is seed, which has a negative correlation, which could be linked to higher seed rates resulting in lower quality and a lower price (Granger, 2018). Total earnings from environmental payments had a positive association with yields. The assumption could be made that this is the result of larger farms having more options and the ability to earn more through environmental schemes.

For financial output per hectare (regression table 4), the relationship remains the same with the inputs. Both the techniques of precision farming and green manure usage had a positive impact. As mentioned previously concerning precision farming, this could be because of larger farms having the ability to utilise the techniques with low risks. However, this positive influence could also be attributed to the benefits provided by green manures (gov.uk, 2021, DAERA, 2021) and precision farming (Pimental and Burgess, 2014; Soto et al. 2019; Balafoutis et al. 2017).

## 3.4 Regression Results: Sustainability metrics

### 3.4.1 Nitrogen-based emissions

*Farm Level: Regression table 5*
For the initial farm level model including activities and inputs the following variables were found to have significant positive association: cereals area ($p<0.01$, 1.667), CPP ($p<0.01$, 0.00036) and gas usage ($p<0.01$, 0.00426). Seed costs ($p<0.01$, -0.00288) were found to have significant negative association. This model has an R-squared value of 0.797.
No demographic or decisions-based data added anything to the model.

Finally adding in farm characteristics data to the initial model found one category of the farms land grade data to be significant and have a positive association ($p<0.05$, 2.092). Areas with a higher quantity of Grade 5 listed land have higher nitrogen-based outputs, but only if the other grade variables are included also. This model has an R-squared value of 0.801

*Per Hectare: Regression table 6*

For the initial 'per Hectare' model including activities and inputs the following variables were found to have significant positive association: Machinery ($p<0.01$, 0.0759), contract ($p<0.05$, 0.0562) and crop protection ($p<0.01$, 0.489). This model has an R-squared value of 0.278.

Adding in the demographics and decision-making data found that the following variables held significant positive association: use of precision agriculture ($p<0.05$, 23.92), and the source of knowledge for crop nutrition ($p=0.05$, 46.05). LEAF membership ($p<0.01$, -51.3) and green manure usage ($p<0.05$, -36.86), were found to have significant negative association. This model has an R-squared value of 0.321.

Finally adding in farm characteristics data to the initial model found one category of the farms land grade data to be significant and have a positive association ($p<0.01$, 1.614). Areas with a higher quantity of Grade 5 listed land have higher nitrogen-based outputs, but only if the other grade variables are included also. Adding in this land grade data moves source of knowledge to have a more significant impact ($p<0.05$, 48.23). This model has an R-squared value of 0.336.

*Per tonne: Regression Table 7*

For the initial 'per Tonne' model including activities and inputs the following variables were found to have significant positive association: crop protection costs ($p<0.01$, .00339), gas usage ($p<0.01$, .0245), machinery ($p<0.01$, .000611) and contract usage ($p<0.01$, .00065). Environmental payments ($p<0.01$, -.00128) were found to have significant negative association. This model has an R-squared value of 0.646.

Adding in the demographic and decision data found significant positive association in the source of knowledge ($p<0.05$, 0.0647). Green manure usage ($p<0.01$, -0.0557) and LEAF membership ($p<0.05$, -0.0545) were found to have significant negative association. Including these dropped the significance of the variable's gas usage and environmental payments. This model has an R-squared value of 0.635.

Finally adding in farm characteristics data to the initial model found one category of the farms land grade data to be significant and have a positive association ($p<0.05$, 0.0017). Areas with a higher quantity of Grade 5 listed land have higher nitrogen-based outputs, but only if the other grade variables are included also. This model has an R-squared value of 0.641.

### 3.4.2 Direct Emissions

*Farm Level: Regression table 8*

For the initial farm level model including activities and inputs the following variables were found to have significant positive association: cereals area ($p<0.01$, 1.491), crop protection costs ($p<0.01$, 0.00343) and agricultural machinery costs ($p<0.01$, 0.00273). Seed costs ($p<0.01$, -0.00411) was found to have significant negative association. No demographic or decisions-based data added anything to the model. This model has an R-squared value of 0.843.

Neither demographic or decisions-based data nor farm characteristics data added anything significant to the model.

*Per Hectare: Regression table 9*

For the initial 'per Hectare' model including activities and inputs the following variables were found to have significant positive association: CPP ($p<0.01$, 0.0038), contract ($p<0.01$, 0.000839) and machinery costs ($p<0.01$, 0.00245). Environmental payments ($p<0.05$, -.00134) were found to have significant negative association. This model has an R-squared value of 0.410.

Adding in the demographic and decision data found significant positive association in the use of precision farming ($p<0.05$, 0.0271) and significant negative association with LEAF membership ($p<0.01$, -0.489). This model has an R-squared value of 0.426.

Finally adding in farm characteristics data to the initial model found one category of the farms land grade data to be significant and have a positive association ($p<0.01$, 0.0154). Areas with a higher quantity of Grade 5 listed land have higher carbon equivalent outputs. Significance was maintained if including all grade data or just grade 5 though influence is lowered in the latter scenario ($p<0.05$, 0.0136). The model including all grade data has an R-squared value of 0.445, whilst the model only including the grade 5 area has an R-squared value of 0.436.

Environmental payments are only significant in the first ($p<0.05$, -0.00134) and third iterations ($p<0.05$, -0.0013) of the model, either only including the other initial variables or including all land grade data.

*Per tonne: Regression table 10:*

For the initial 'per Tonne' model including activities and inputs the following variables were found to have significant positive association: seed costs ($p<0.01$, 0.00424), crop protection costs ($p<0.01$, 0.0039), machinery usage ($p<0.01$, 0.00435) and contract expenses ($p<0.01$, 0.00192). Environmental payments ($p<0.01$, -0.00378) and electricity usage ($p<0.01$, -0.00578) were found to have significant negative association. This model has an R-squared value of 0.883.

Adding in the demographic and decision data found significant positive association with the use of precision farming ($p<0.01$, 0.0386). Green manure usage ($p<0.05$, -0.0524) and LEAF membership ($p<0.05$, -0.0708) were found to have significant negative association. The variable of electricity usage became insignificant once these were added. This model has an R-squared value of 0.888.

Finally adding in farm characteristics data to the initial model found one category of the farms land grade data to be significant and have a positive association ($p<0.05$, 0.00218). Areas with a higher quantity of Grade 5 listed land have higher carbon equivalent outputs, but only if the other grade variables are included also. The variables of precision farming, green manure usage and LEAF membership each dropped to insignificant with the inclusion of farm grades in the third model. This model has an R-squared value of 0.883.

<u>Regression results table – Sustainability metrics</u>

The results are presented below with the coefficient represented, the standard errors in parentheses, and the p value given an approximation through a scale of asterisk's (*** p<0.01, ** p<0.05). Variables with a p value of more than the required 0.05, but are a part of a categorical set, are presented in bold and underlined.

### 3.4.3 Nitrogen-based Emissions

*Regression table 5:*

| VARIABLES | Model 1<br>Farm Level Nitrogen emissions | Model 3<br>Farm Level Nitrogen emissions |
|---|---|---|
| Cereals area | 1.667*** | 1.618*** |
| | (0.191) | (0.193) |
| Seed | -0.00288*** | -0.00270** |
| | (0.00104) | (0.00106) |
| Crop Protection Products (CPP) | 0.00360*** | 0.00370*** |
| | (0.000587) | (0.000588) |
| Gas expense | 0.0426*** | 0.0434*** |
| | (0.0164) | (0.0164) |
| Land Grade 2 | | **<u>0.140</u>** |
| | | **<u>(0.384)</u>** |
| Land Grade 3 | | **<u>0.291</u>** |
| | | **<u>(0.285)</u>** |
| Land Grade 4 | | **<u>0.0485</u>** |
| | | **<u>(0.438)</u>** |
| Land Grade 5 | | 2.092** |
| | | (0.994) |
| Constant | 11.40 | -50.67 |
| | (13.73) | (78.53) |
| Observations | 336 | 336 |
| R-squared | 0.797 | 0.801 |

*Land Grade base: quantity of land graded 1 on farm*

*Regression table 6:*

| VARIABLES | Model 1<br>Per ha Nitrogen emissions | Model 2<br>Per ha Nitrogen emissions | Model 3<br>Per ha Nitrogen emissions |
|---|---|---|---|
| Machinery/ha | 0.0759*** | 0.0792*** | 0.0737*** |
| | (0.0229) | (0.0229) | (0.0231) |
| Contract/ha | 0.0562** | 0.0570** | 0.0591** |
| | (0.0278) | (0.0276) | (0.0276) |
| CPP/ha | 0.489*** | 0.440*** | 0.451*** |
| | (0.0517) | (0.0540) | (0.0542) |
| Precision farming – Yes – 2 | | 23.92** | 26.18** |
| | | (12.03) | (12.02) |
| Precision farming – Partial – 3 | | <u>20.81</u> | <u>21.50</u> |
| | | <u>(21.78)</u> | <u>(21.72)</u> |
| Precision farming – N/A – 4 | | <u>-65.66</u> | <u>-60.68</u> |
| | | <u>(75.27)</u> | <u>(75.36)</u> |
| Green manure usage - Yes | | -36.86** | -32.51** |
| | | (16.02) | (16.14) |
| Green manure usage - Partial | | <u>13.29</u> | <u>17.02</u> |
| | | <u>(30.18)</u> | <u>(30.35)</u> |
| Source of knowledge - 2 | | <u>46.05</u> | 48.23** |
| | | <u>(23.41)</u> | (23.36) |
| Source of knowledge - 3 | | <u>17.45</u> | <u>16.78</u> |
| | | <u>(15.71)</u> | <u>(15.67)</u> |
| Source of knowledge - 4 | | <u>10.12</u> | <u>13.54</u> |
| | | <u>(17.53)</u> | <u>(17.50)</u> |
| LEAF member - Yes | | -51.30*** | -49.63*** |
| | | (18.48) | (18.45) |
| Land Grade 2 | | | <u>0.194</u> |
| | | | <u>(0.229)</u> |
| Land Grade 3 | | | <u>0.169</u> |
| | | | <u>(0.170)</u> |
| Land Grade 4 | | | <u>0.0960</u> |
| | | | <u>(0.264)</u> |
| Land Grade 5 | | | 1.614*** |
| | | | (0.607) |
| Constant | 86.75*** | 82.56*** | 32.40 |
| | (16.70) | (20.11) | (50.26) |
| Observations | 336 | 336 | 336 |
| R-squared | 0.278 | 0.321 | 0.336 |

*Green manure base: 1/does not use green manures*

*Source of Knowledge base: 1/own knowledge (no FACTS qualification)*

*LEAF member base: 1/no LEAF membership*

*Land Grade base: quantity of land graded 1 on farm*

*Regression model 7:*

| VARIABLES | Model 1<br>Per tonne<br>Nitrogen emissions | Model 2<br>Per tonne<br>Nitrogen emissions | Model 3<br>Per tonne<br>Nitrogen emissions |
|---|---|---|---|
| CPP/t | 0.00399*** | 0.00462*** | 0.00472*** |
| | (0.000512) | (0.000493) | (0.000495) |
| Machinery/t | 0.000611*** | 0.00125*** | 0.00123*** |
| | (0.000201) | (0.000103) | (0.000103) |
| Contract/t | 0.000650*** | 0.000706*** | 0.000730*** |
| | (0.000250) | (0.000226) | (0.000227) |
| Green Manure Usage – Yes – 2 | | -0.0557*** | -0.0514** |
| | | (0.0198) | (0.0200) |
| Green Manure Usage – Partial - 3 | | <u>**0.0333**</u> | <u>**0.0380**</u> |
| | | <u>**(0.0373)**</u> | <u>**(0.0376)**</u> |
| Source of knowledge – 2 | | 0.0647** | 0.0669** |
| | | (0.0286) | (0.0287) |
| Source of knowledge – 3 | | <u>**0.0282**</u> | <u>**0.0277**</u> |
| | | <u>**(0.0191)**</u> | <u>**(0.0191)**</u> |
| Source of knowledge – 4 | | <u>**0.0235**</u> | <u>**0.0269**</u> |
| | | <u>**(0.0213)**</u> | <u>**(0.0213)**</u> |
| LEAF member – Yes | | -0.0545** | -0.0512** |
| | | (0.0226) | (0.0227) |
| Land Grade 2 | | | <u>**0.000113**</u> |
| | | | <u>**(0.000284)**</u> |
| Land Grade 3 | | | <u>**0.000147**</u> |
| | | | <u>**(0.000210)**</u> |
| Land Grade 4 | | | <u>**5.86e-06**</u> |
| | | | <u>**(0.000324)**</u> |
| Land Grade 5 | | | 0.00170** |
| | | | (0.000751) |
| Gas/t | 0.0245*** | | |
| | (0.00663) | | |
| Environmental payments/t | -0.00128*** | | |
| | (0.000417) | | |
| Constant | 0.131*** | 0.0539** | 0.0139 |
| | (0.0210) | (0.0213) | (0.0612) |
| Observations | 336 | 336 | 336 |
| R-squared | 0.646 | 0.635 | 0.641 |

*Green manure base: 1/does not use green manures*

*Source of Knowledge base: 1/own knowledge (no FACTS qualification)*

*LEAF member base: 1/no LEAF membership*

*Land Grade base: quantity of land graded 1 on farm*

### 3.4.4 Direct Emissions

*Regression table 8:*

| VARIABLES | Model 1<br>Farm Level<br>Direct emissions |
|---|---|
| Cereals area | 1.491*** |
| | (0.202) |
| Seed | -0.00411*** |
| | (0.00112) |
| Crop Protection Products (CPP) | 0.00343*** |
| | (0.000605) |
| Machinery | 0.00273*** |
| | (0.000267) |
| Constant | -19.24 |
| | (14.78) |
| Observations | 336 |
| R-squared | 0.843 |

*Regression table 9:*

| VARIABLES | Model 1<br>Per ha Direct emissions | Model 2<br>Per ha Direct emissions | Model 3<br>Per ha Direct emissions | Model 3.5<br>Per ha Direct emissions |
|---|---|---|---|---|
| Machinery/ha | 0.00245*** | 0.00241*** | 0.00239*** | 0.00237*** |
| | (0.000232) | (0.000231) | (0.000232) | (0.000230) |
| Contract/ha | 0.000839*** | 0.000738*** | 0.000876*** | 0.000765*** |
| | (0.000288) | (0.000279) | (0.000285) | (0.000278) |
| CPP/ha | 0.00380*** | 0.00378*** | 0.00362*** | 0.00383*** |
| | (0.000540) | (0.000535) | (0.000548) | (0.000532) |
| Environmental payments/ha | -0.00134** | | -0.00130** | |
| | (0.000637) | | (0.000636) | |
| Precision farming – Yes - 2 | | 0.271** | 0.298** | 0.297** |
| | | (0.121) | (0.121) | (0.121) |
| Precision farming – Partial - 3 | | 0.170 | 0.186 | 0.195 |
| | | (0.219) | (0.218) | (0.218) |
| Precision farming – N/A - 4 | | -1.382 | -1.183 | -1.324 |
| | | (0.749) | (0.749) | (0.744) |
| LEAF member – Yes | | -0.489*** | -0.460** | -0.471** |
| | | (0.186) | (0.185) | (0.184) |
| Land Grade 2 | | | 0.00186 | |
| | | | (0.00229) | |
| Land Grade 3 | | | 0.00199 | |
| | | | (0.00170) | |
| Land Grade 4 | | | 0.00126 | |
| | | | (0.00265) | |
| Land Grade 5 | | | 0.0154** | 0.0136** |
| | | | (0.00608) | (0.00573) |
| Constant | 0.789*** | 0.685*** | 0.251 | 0.636*** |
| | (0.177) | (0.173) | (0.490) | (0.173) |
| Observations | 336 | 336 | 336 | 336 |
| R-squared | 0.410 | 0.426 | 0.445 | 0.436 |

*Precision farming base: 1/no use of precision farming techniques*

*LEAF member base: 1/no LEAF membership*

*Land Grade base: quantity of land graded 1 on farm*

*Regression table 10:*

| VARIABLES | Model 1<br>Per tonne Direct emissions | Model 2<br>Per tonne Direct emissions | Model 3<br>Per tonne Direct emissions |
|---|---|---|---|
| Seed/t | 0.00424*** | 0.00509*** | 0.00405*** |
| | (0.00104) | (0.00106) | (0.00105) |
| CPP/t | 0.00390*** | 0.00327*** | 0.00417*** |
| | (0.000705) | (0.000725) | (0.000709) |
| Machinery/t | 0.00435*** | 0.00404*** | 0.00407*** |
| | (0.000240) | (0.000225) | (0.000231) |
| Contract/t | 0.00192*** | 0.00178*** | 0.00182*** |
| | (0.000341) | (0.000334) | (0.000342) |
| Environmental payments/t | -0.00378*** | -0.00361*** | -0.00378*** |
| | (0.000590) | (0.000586) | (0.000602) |
| Precision farming – Yes – 2 | | 0.0386** | |
| | | (0.0193) | |
| Precision farming – Partial – 3 | | 0.0185 | |
| | | (0.0348) | |
| Precision farming – N/A – 4 | | -0.380*** | |
| | | (0.123) | |
| LEAF member – Yes | | -0.0708** | |
| | | (0.0296) | |
| Green manure usage – Yes – 2 | | -0.0524** | |
| | | (0.0261) | |
| Green manure usage – Partial - 3 | | 0.0114 | |
| | | (0.0489) | |
| Electricity/t | -0.00578*** | | |
| | (0.00203) | | |
| Land Grade 2 | | | 0.000204 |
| | | | (0.000376) |
| Land Grade 3 | | | 0.000278 |
| | | | (0.000279) |
| Land Grade 4 | | | -0.000130 |
| | | | (0.000434) |
| Land Grade 5 | | | 0.00218** |
| | | | (0.000994) |
| Constant | -0.0631*** | -0.0566** | -0.132* |
| | (0.0234) | (0.0257) | (0.0789) |
| Observations | 336 | 336 | 336 |
| R-squared | 0.883 | 0.888 | 0.883 |

*Precision farming base: 1/no use of precision farming techniques*

*Green manure base: 1/does not use green manures*

*LEAF member base: 1/no LEAF membership*

*Land Grade base: quantity of land graded 1 on farm*

## 3.5 Results interpretation: Sustainability metrics

### 3.5.1 Nitrogen-based emissions

Inputs had a positive association with total nitrogen-based outputs (regression table 5) except for seed expenses. The more land that is devoted to cereals, the more fertilizer is needed and emissions occur, leading to cereals area having a positive impact on this model. Grade 5 land classification has a positive association nitrogen-based output, meaning that areas with a higher quantity of low-grade land have higher nitrogen emissions. This could be explained by the need for more fertiliser on low grade land to improve yields and financial output, as grade 5 is defined as requiring action to make productive (MAFF, 1988).

When measuring at a per hectare level (regression table 6) the significant inputs also had a positive impact on nitrogen-based emissions. In this model, farms implementing precision techniques were emitting higher quantities of nitrogen-based emissions. An assumption could be made that this is because precision agriculture is largely being adopted for financial and output purposes, or for another environmentally conscious reasons and not to decrease emissions (Godwin et la. 2003a). The environmentally focused decisions of LEAF membership and green manure usage led to decreases in nitrogen emissions per hectare. Persons who are FACTS qualified, and taking their own advice, have a higher output of nitrogen emissions. It could be assumed that not taking external advice could lead to over-application of nitrogen because of previously successful results, leading to a generally higher usage of fertilizers and therefore a higher output of nitrogen emissions. The quantity of grade 5 land positively impacts this model again.

At the per tonne level (regression table 7) inputs also had a positive influence over emissions. Environmental payments, green manure usage and leaf membership all caused a decrease in nitrogen emissions per hectare. This is expected, as reduction in harmful emissions is the intent of both decisions (LEAF, 2021). The impact of land grade 5 and the source of nutrition knowledge were both positively significant, whilst precision farming had no effect at the per tonne level. The quantity of grade 5 land also positively impacts this model again.

### 3.5.2 Direct carbon equivalent emissions

Inputs had a positive association with total direct emissions outputs (regression model 8) except for seed expenses. Area devoted to growing cereals increased direct emissions, likely due to the need increasing need for further inputs and machinery usage, as land use also increases.

At the per hectare level (regression table 9) all inputs, and activities had a positive impact on direct emissions, which is to be expected given the need for machinery to carry out these tasks. Both environmental payments and LEAF membership were associated with a reduction in direct emissions per hectare, which could be an intended outcome. Precision farming has an unexpectedly positive impact on this model. This could be again due to the method being used to optimise areas outside of fuel and fertilisers (Godwin et la. 2003a; Pimental and Burgess, 2014). The quantity of grade 5 land has a positive association with the direct emissions per hectare, meaning that areas with a higher quantity of low-grade land have higher nitrogen emissions. This could be explained by the need for more fertiliser and tilling activities on low grade land to improve yields and financial output.

When measuring at a per tonne level (regression model 10) inputs had a positive influence over emissions, except for electricity. This matches with the yield results looking at total tonnes and possibly indicates the use of electricity instead of fuel for certain activities, for example using electric grain dryers instead of gas- or petrol-powered machines. Environmental payments, leaf membership also negatively impacted direct emissions per tonne. Green manure usage negatively affected direct emissions at a per tonne level. The fact that it did not affect direct emissions at a per hectare level indicates that the benefit is from increasing the yield relative to direct emissions rather than decreasing those emissions. This would be because of the benefits provided by this technique (DAERA, 2021). The use of precision farming and the quantity of grade 5 land both positively impact this model again.

## 4.0 Discussion

### *4.1 Level of Measurement*

Measuring per hectare removes the noise created by the influence of total size. At a farm level, as the farmland used increases, every input inherently has the potential to increase. Analysis at a per hectare level allows for the comparison of the efficiency of each farm's use of the same hectare, regardless of the total land available to them. A future consideration or improvement on the models presented here, would be to look at the specific differences to models at a farm level created both with and without farm area included. Measuring at a per tonne level also observes what a farm uses to get the same tonne of produce.

Many international governing bodies recommend calculating based on amount of equivalent carbon produced per hectare (DPIRD, 2021; EPA, 2021; FAO, 2021). But this ignores the food security issue presented by only observing land usage and not production. Because of the different aspects of efficiency explored by each measurement (input or land usage versus output). Being highly efficient from a hectare perspective may compromise yields and therefore food security yet have the appearance of a positive result when measured at this level. The same can occur with being highly efficient in tonnes produced, where it may come at the cost of permanent environmental damage, but again presents as a positive result at the per tonne level. Successful sustainable intensification demands the examination of both aspects.

### *4.2 Location, climate, and environment*

Using the JCA codes yielded insignificant results. This could be linked to a limitation within the dataset where the high quantity of categories (366 farms being spread across 92 of 152 codes) plus the lack of data attached to those categories, limits the readability of the data. In the dataset the categories are discrete, whereas in reality, the characteristics of land change continuously and gradually.

Other studies have previously had issue with the environmental variables that affect GHG emissions, and the specific carbon equivalent multiplier used for fertiliser-sourced emissions in this study. The IPCC tier 1 estimates used for emissions (Sykes et al, 2017) have been criticised for their simplicity and lack of specificity (Cardenas et al., 2013). Aspects like the fertiliser type used, soil acidity and temperature are not accounted for (Chadwick et al., 2011; Shen et al., 2018; Taft et al., 2017). Further studies have found that this multiplier fails to accurately reflect the influence of climate and landscape on emissions from fertilisers (Cardenas et al., 2013; Tian et al., 2017).

Similarly, the multipliers for carbon emissions do not factor in the nuances of their creation. The equation used for both fuel and fertiliser output takes the total input and multiplies it by a broad estimate of the emissions produced per unit. In this instance that end figure is multiplied to give a carbon equivalent amount. The efficiency of each farm's fuel consumption is unknown and assumed by the multiplier, in the same way that the local climate, soil characteristics and practice that impact nitrous oxide output are assumed within the fertiliser carbon equivalent calculator. In reality, fuel consumption and emissions differ from machine to machine and changes through the way it is used (Zacharoff & Fontaras, 2016). The same occurs with fertiliser use, where practices, climate and soil conditions all impact emissions (Krol et al., 2016; Oertel et al. 2016; Hungria et al., 2009). A limitation of the nature of these multipliers used in this research is that the only input to the equation that is relevant to each individual farm is the resource input itself and not the usage. Therefore, the only place for examination and change is this input. Alternatively, the model could be showing that there is no influence from local conditions on GHG emissions and production. But this is contrary to the literature and study surrounding the subject (Butterbach-Bahl et al. 2013; Krol et al., 2016).

A final aspect to consider is the nature of farming itself and the impact it has on the local conditions that these models were attempting to observe. Farmers deal with homogenous products produced from non-homogenous circumstances. The actions taken in production aim to homogenise the environment of their land to create the best conditions to produce cereals. The data may not reflect the environment that the crops were produced in because the farmers have successfully offset its impact on cropping through practices and levels of crop production inputs.

*4.3 Soil properties*

The data used from the CEH proved insignificant. However, the data on the quantity of each land grade present in each farm's area proved significant in several of the models. This indicates that some aspects of land quality, and therefore soil properties, were observable within the dataset used.

For the emissions models, farms with a higher quantity of Grade 5 land in their area had higher emissions. Grade 5 is not typically used for cereals, so areas with higher Grade 5 are not typical cereal growing areas. This could point to farms in these areas not being typical cereal farms and being less efficient with inputs, the land being of lower quality and thus requiring overcompensation and thus resulting in inefficiencies in production.

Whereas for financial output, Grades 3 and 4, the typical cereal grades for lower quality cereals, had lower outputs than the base grade of 1, indicating that lower land grade quality leads to lower financial output. Overall, this indicates that further data applied to the sorting system of the JCA, could lead to more significant results. Further data could be attached to JCA or CEH codes, such as giving a numerical value to slopes for topography or attaching a new area, such as average rainfall or a similar climatic factor known to be significant to GHG output (Krol et al., 2016; Clarke and Fraser, 2004; Hungria et al., 2009). The use of each JCA codes average Land grade proportions is a limitation with this research that could be improved upon with on farm data about the soil properties or land grades present.

Factors discussed within the literature review, such as climate and soil properties, also inform the land classification code given for an area. This includes the nutritional and chemical characteristics of soil (MAFF, 1988) which are known to impact emissions (Taft et al., 2017; Gao et al. 2020; Sanbayram et al. 2019). CEH classifications document the topography of the farm, a factor that both affects GHG emissions and is not accurately accounted for within the IPCC estimations (Cardenas et al. 2013), presenting another limitation on the results of this research.

The influence of the different grades of land was shown across many models, always with the indication that lower grade soils performed poorly or had a negative association in comparison with the highest grade, used as the base in the models. This indicates the importance of the influence of the conditions that the crops are grown in. An implication of this, is that farms with lower quality/graded land, which already have commercial outputs, may struggle financially if pressured to further reduce GHG emissions.

A potential future development would be to use a different level of carbon calculation. The current tier 1 is described a non-specific default emissions factor, that is based on inputs. Tier's 2 and 3 of the IPCC each offer further detail to close the gap between the accuracy of the calculations and the on-farm reality of GHG emissions (Feliciano, et al., 2017). Tier 2 uses a region or climate specific equation, that incorporates activities performed in its calculations. This would account for the lost influence of local climate and weather on GHG emissions (Cardenas et al., 2013; Tian et al., 2019). Tier 3 estimates offer further details, using local area plot data in its calculations (Feliciano, et al., 2017). Tier 3 is also the only level that incorporates soil-carbon dynamics (Feliciano, et al., 2017).

Overall, the SIP carbon accountancy (benchmarkmyfarm.co.uk, 2021) currently stands a useful tool to benchmark input usage efficiency and to encourage action to reduce GHG outputs. However, further research based on the farms specific conditions will be needed to correctly inform practice changes. It does not have enough specificity to correctly identify methods to reduce GHG outputs, besides the reduction of inputs. A future improvement could be to use a calculator with a higher tier of the IPCC method or to encourage the collection of on farm data to compare to the benchmark created by these multipliers.

### *4.4 Practices and decisions*

In general higher inputs led to greater outputs. The exception to this across the models has been the influence of seed costs. Higher seed rates than necessary can negatively impact aspects affecting yield, such as disease resistance and lodging (the crop falling over) (Granger, 2018, Cheema et al. 2003). This offers explanation to the models results of a generally negative association with outputs.

Regarding practices, machinery and contract usage costs were consistently significant across the per hectare and per tonne GHG models, having an expected positive relationship with emissions. Higher machinery usage leads to higher use of fuels by necessity. This also implies more activities being performed, such as fertilizer application, again leading to higher outputs of GHG's. This use in turn incurs costs for maintenance and replacement over time, leading to this relationship. Likewise, higher contract costs indicate higher machinery usage. However, both variables had a negative impact on yields, which could be assumed as the influence of smaller farms, which are more likely to use contractors and have higher machinery costs in comparison to output.

Decisions involving pure environmental motivations had a reductive influence on emissions, showcasing that they are working as intended (LEAF membership and expense on environmental services). There were further interesting results for the specific environmentally focused techniques of precision agriculture and green manure usage.

Precision farming is often presented as a method to reduce the carbon emissions of farms (Soto et al. 2019). When it comes to inputs, the ability to vary the rates of application is a key tool in precision agriculture. Variable rate application refers to changing the quantity of a product applied depending on the need for that product (Dusadeerungsikul et al. 2020). For example, pesticide rates based upon higher or lower incidences of pests and disease within the field.

Regarding fertilisers and precision farming, Godwin et al. (2003b) showcased its use through variable rate application. This involved applying more fertiliser on areas experiencing lower fertility and less on areas of high fertility. The increase in productivity produced by this method correlates with the results of this research, showing that using this precision method increases yields and overall financial outputs from cereals. This corroborates with the FBS data on farms implenting precision farming techniques.

However, Godwin et al. (2003b) experienced a reduction of a third of fertiliser quantity used, reducing the amount of nitrous oxide available to be emitted. This is supported by Balafoutis et al. (2017) where precision techniques such as variable rate nutrient application and irrigation were found to significantly reduce usage and mitigate nitrous oxide emissions.

An explanation of this is that precision farming can be used to tackle a broad range of issues, including productive aspects, but also environmentally conscious ones that do not involve the significant reduction of GHG's. Reducing pesticides through precision techniques benefits the environment by the reduction and precision of its application (Pimental and Burgess, 2014), but will leave the GHG output of a farm unchanged (Croplife, 2012). Because of the wide-ranging applications of precision farming, this implies that the cereal farms covered in the FBS 2017 dataset which are using the techniques are not doing so in way to reduce inputs such as fossil fuel or nitrogen fertilisers, but instead to improve outputs or provide other environmental benefits.

Green manure usage, which is described similarly as mitigating GHG emissions (DAERA), 2021, was observed to have significant influence within the models created as part of this research. Green manures are plants grown with the explicit purpose of maintaining soil structure and fertility between commercial cropping (DAERA, 2021). They negate some of the need for inputs, such as nitrogen fertilizer (DAERA, 2021). Because of this, lower emissions are derived from fertilisers, explaining the results. They also positively influence the financial output of farms, indicating higher quality or quantity of produce from farms using green manures. Green manure usage and cover cropping are often used interchangeable (Dyer, 2021). The difference between them is that cover crops are harvested, whilst green manures are incorporated into the soil (gov.uk, 2021). Cover cropping is currently being promoted as a method of sustainable practice to maintain soil health (DAERA, 2021), and green manures are no different. During the lifespan of cover crops and green manures, or up until the respective harvest and incorporation, both perform similar functions and have similar benefits (gov.uk, 2021).

Despite both the approaches of green manures and precision farming being pushed as GHG mitigating methods, the analysis performed on FBS data from 2017 showcases very different outcomes. Overall uptake for precision farming is better than green manure usage, with 44 percent of farms in this dataset implementing precision farming (see table 3), but the data implies that its implementation has not mitigated emissions, instead, farms that have implemented it have higher emissions than those that have not. Because of this and the previous assumptions that precision agriculture reduces GHG emissions, there is the danger of the interpretation of a high uptake of a GHG mitigating activity across the UK and therefore a high level of GHG mitigation. Only 17 percent of farms in the sample have implemented green manures (see table 3), indicating the desired negative impact on emissions.

As outlined previously, the SIP multipliers are best suited to comparing resource usage and not for deriving consequences, such as carbon equivalent outputs. However, for the two variables of green manure usage and precision farming, reducing resource usage is the desired and predicted outcome (Soto et al. 2019; Balafoutis et al. 2017; Godwin et al., 2003a). Therefore, the SIP calculators can effectively serve the purpose of monitoring techniques that aim to be more resource efficient. For example, an interesting way to develop this finding would be to observe the relationships between precision farming and other resources, such as pesticides and irrigation.

A limitation of the research presented here is that it is concentrated on a single year (2017). It is possible that farms otherwise utilising precision farming to reduce emissions had to adapt in this given year because of unknown variables, such as the weather. Further research should be undertaken to observe trends over a longer period to better assess the relationships between precision techniques and its consequences on inputs and outputs. As outlined with precision agriculture, a further limitatin is the lack of specificity with the information on specific activities. For example, the form of precision used or the specific uses of green manures within the rotations.

The FBS concentrates on inputs and outputs, but further collection of information concerning specific practices could showcase the efficacy, or lack thereof, of techniques with the purpose of making resource usage more efficient in the UK. This could expand from current examples such as precision farming, green manures or nutrient software use, to include aspects of tillage (minimum or no-till systems), cover cropping, or use of NIs.

*4.5 Evaluating and measuring Sustainable Intensification*

Sustainable intensification is loosely defined as using the same land to produce more, whilst reducing environmental impacts (Struik and Kuyper, 2017; Dicks et al., 2020). The aim is to evaluate eco-efficiency, or how efficient a natural resource is being used to meet human needs (Dicks et al. 2020). This broad definition allows for a variety of approaches, not just to implementation, but to measurement and evaluation (Dicks et al., 2020, Mahon et al. 2016, Gunton et al. 2016). Evaluation is performed observing the desired consequences of a farm (resource output, eco-system services), comparing this with the undesired consequences (emissions, environmental damage, use of inputs) (Dicks et al., 2020). The primary choice made is which consequences to measure and compare.

Focusing on a single area of improvement may compromise other eco-system services, leading to a net negative result. One example of this single factor use being limited, is the result of precision agriculture in this paper. The face-value conclusion is that this has a negative or neutral impact on GHG emissions and therefore sustainable intensification, despite literature to the contrary. Measuring other aspects of sustainability on these farms would likely reveal its benefits.

Alternatively, results may show a technique or attitude contributing to the apparent sustainability of the entire system but is a neutral or damaging approach to a specific area. Despite being an easily readable indicator, presenting a single wide-spanning metric on sustainable intensification removes the impact of individual circumstances, especially due to variation of productive conditions and financial pressures within a single year (Petersen and Snapp, 2015). It also does not allow for the concept that land may be better converted to another ecological use, besides agriculture. However, it does allow for targeted approaches, with the research presented here showcasing potential use for a single metric.

The alternative approach is to create a metric that incorporates several indicators, or even modelling for all. This creates issues with over fitting and individual factors can be missed, due to issues of offsetting. A farm can choose to prioritise intensification and get a better than average index, with many parties presenting this as more efficient for sustainable intensification (Struik and Kuyper, 2017; Gadanakis et al. 2015). Barnes and Thomson (2014) noted this as a weakness and concluded that this is an issue with the definition of sustainable intensification, where societal and ethical factors are not integrated despite being key tenets in wider sustainability. Social aspects such as gender equity are further important metrics of sustainability but are often noticeably absent from literature evaluating sustainable intensification (Smith et al., 2017).

Overall, tighter definitions of sustainable intensification are needed and there are already calls for this (Smith et al. 2017). These definitions must incorporate all aspects of sustainability, not just commercial and ecological, but social. This will allow more consistent measurements and evaluation of sustainable intensification, leading to long-term global food security whilst limiting damage to natural resources. Analysing metrics incorporating these indicators can provide a gauge to overall progress, whilst individual markers can highlight important issues, such as GHG emissions, to address immediate problems.

*4.6 The Sustainable Intensification of farming systems*

The nature of sustainable intensification allows a farm with a high negative externality, such as low diversity, high emissions, or a heavy reliance on chemicals to offset these results with high productivity (Gadanakis et al., 2015), leading to the concept being labelled as an oxymoron in some instances (Mahon et al., 2017; Smith et al. 2018). Farm systems focusing on income are the most effective target of sustainable intensification (Struyk and Kuyper, 2017). Jourdain et al. (2020) note that they are less likely to uptake such attitudes unless they can be convinced of its efficacy without compromising said income.

The idea of combining the issues of immediate food security and long-term ecological stability may limit the ability of the swift progress necessary for the latter issue and compromise the former in the future. As previously noted, a farm can choose to prioritise intensification to improve efficiency (Struik and Kuyper, 2017), rather than contribute to the very immediate needs of reduction. An alternative approach would be to encourage pure reduction, rather than comparative reduction.

A question asked by the literature is whether the intensification side necessary at all. In 2018, approximately £19 billion worth of food waste was produced in the UK alone (WRAP, 2020). The sector of cereal production makes up the largest proportion of this at 31% (Jeswani et al. 2021). Struik and Kuyper (2017) suggest the definition be split into the intensification of current low-output agriculture, specifically referencing the global south where intensification is not only necessary but inevitable, whilst also encouraging the de-intensification of high-output agriculture, to further prioritise eco-system services. Considering that a level of intensification is needed to feed the growing population (Firbank, 2020), this allows for this to occur globally but without putting further pressure on already intensely farmed areas.

An alternative suggestion by Gunton et al. (2016) is that definition be changed to maintaining or enhancing the provision of agricultural services, whilst at the same time maintaining or enhancing the eco-systems services provided. This would reduce the importance of intensification and ability of farms to offset damages, rather than fix them. Offsetting permanently damaging issues with temporary provisions to the UK food supply chains.

The concept of sustainability as an important one that must be brought to the forefront of UK agricultural practices. However, the necessity of intensification in the UK is debatable. Sustainable intensification can provide many benefits if successful, but because of the fluid nature of its definition, certain interpretations are flawed and can lead to net negative results.

*4.7 Conclusion*

Reducing emissions and increasing food output is an important goal for agriculture in the 21st century. Carbon accounting and resource use efficiency tools including the SIP benchmarking system have their place in aiding this goal and increasing awareness. As this research has shown, it is possible to develop commentary about the practices of UK farms and their impact. However, several areas were also highlighted for improvement or further development.

The level of measurement used impacts the outcomes of any analysis and observations. Per hectare is used as standard (DPIRD, 2021; EPA, 2021; FAO, 2021), but per tonne offers alternative comparison, especially with the need for sustainable intensification. Likewise, total contribution is an important characteristic and reduction in GHG emissions should be pursued any place that it is possible. A suggestion for future research and observation of UK farming GHG output is to collect and compare multiple measures, to better inform decision making rather than focusing on a single metric. Efficiency of resource production against GHG outputs is important alongside efficiency of resource use.

The current carbon equivalency model used in this research has limited efficacy, due to the simplicity of it. To be easily used, it sacrifices accuracy and does not account for the variation in results caused by the diverse factors affecting farmland. It also only accounts for direct emissions from fertilisers and fuel, not including soil carbon respiration or methane output of manures used in otherwise arable systems. Utilising a more advanced model could improve the results. For example, IPCC tier 2 calculations which incorporate greater detail on activities and location, or tier 3 which also includes soil carbon dynamics (Feliciano, et al., 2017). All models come with a compromise, therefore a further suggestion would be to encourage on location testing for individual farmers, to compare real results to the derived national averages. If incorporated into a government scheme, this could lead to a national database on agricultural GHG emissions with greater detail and therefore greater ability to make informed decision and actions to reduce the inventory.

An extension of this suggestion of further detail to the model is the inclusion of further detail about the physical characteristics of the farm. Whilst the categorical codes representing the location of the farm proved insignificant, the continuous data on each areas land grade provided interesting results. Further inclusion of details about farm characteristics could better inform farmers, researchers, and policymakers on which GHG mitigating techniques to utilise or encourage in the future. This could entail making the land grade data in this study farm specific, rather than JCA code specific, or collecting information on other characteristics known to influence GHG's, such as rainfall or topography (Krol et al., 2016; Clarke and Fraser, 2004; Hungria et al., 2009).

The benchmarking models proved useful for monitoring and benchmarking input efficiency when it comes to novel techniques aimed at reducing such inputs. The addition of further survey information would benefit other farmers and policymakers, by showcasing the activities resulting in better resource management and those that are not. A suggestion from this would be to add more questions regarding specific techniques in the FBS. For example, including questions about cover cropping, or expanding the precision farming category to include which production area is utilising this method, e.g. fertiliser, seed or spraying.

There are limitations to the methods and resources used within this study. There are also areas that could benefit from expansion. However, understanding the externalities produced by farming are essential to it sustainability as an industry and ability as a food provider. Platforms such as the SIP’s benchmarking tool (benchmarkmyfarm.co.uk, 2021) contribute information to aid in both these aspects. Further expansion of the detail, scope and use for carbon calculators like these will help to inform the future decisions made by farmers, researchers, and policymakers, that will aid in the reduction of GHG’s and the sustainability of food production.

## 5.0 Reference list

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