Doctoral Students as Carbon Accountants: Calculating Carbon Costs of a PhD in Neuroscience

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Abstract

Research is an energy and resource-demanding activity. However, despite increasing awareness and emerging sustainability initiatives, a paucity of data and methodological inconsistency continue to hamper effective and accountable emissions mitigation. With > 250,000 doctoral students graduating annually across all academic disciplines, empowering PhD students to engage in carbon accounting could provide a sizable and robust source of carbon data alongside a powerful generational force for decarbonisation. Here, we demonstrate how doctoral students and other researchers can consistently measure the carbon footprint of their work, using one PhD student's research in a neuroscience *Drosophila* lab as our case study. We present a comprehensive life-cycle assessment of the equivalent carbon dioxide emissions (CO_2e) generated by the student's research activities, including measurement of scope 1 emissions associated with *Drosophila* husbandry; calculation of time- and region-specific scope 2 emissions produced by widely used techniques including calcium imaging, electrophysiology, and optogenetics; and estimation of scope 3 emissions associated with procurement and research-related travel. We found that research-related travel and procurement of laboratory supplies were responsible for the majority of annual emissions, up to 1942 kg CO_2e and 543 kg CO_2e respectively after accounting for aircraft radiative forcing. Using NESO's open-source Carbon Intensity API to account for temporal and geographical variation in the carbon intensity of UK National Grid energy, we found that persistent laboratory energy consumption released 10.99 kg CO_2e, with an additional 3.56 kg CO_2e scope 2 and 3.6 kg CO_2e scope 1 emissions underpinning direct research activities. Finally, we discuss the challenges of accurately carbon foot printing research across disciplines in the UK and beyond, highlighting the value of regionally precise open-source energy mix data and the need for data openness within research supply chains. Overall, we present a common framework for including carbon footprint analyses as 'Carbon Appendices' to PhD theses to generate carbon footprint data across disciplines. Beyond the benefits of such data for informed emissions mitigation, we envision doctoral students carrying insights from carbon appendices forward into academia and industry to catalyse a community-driven decarbonisation of the research sector.

Introduction

Greenhouse gas emissions resulting from human activities are a major driver of global warming and climate change. Efforts to systematically reduce and mitigate the effects of excess atmospheric greenhouse gases involve coordinated actions across all sectors of life. Scientific researchers are increasingly considering the environmental impacts of their work. By focusing on "cradle-to-grave" life cycle assessments, institutions (McGain and Naylor, 2014; Valls-Val and Bovea, 2021; Martin *et al.*,

2022) and individual researchers (e.g., Thiel *et al.*, 2017; Gordon *et al.*, 2021; Elli *et al.*, 2024) have begun to account for their direct (scope 1) and indirect (scope 2, via energy production; and scope 3, incorporating all other life cycle emissions not operated or controlled by the user) activity-related carbon emissions, with the goal to mitigate lab activity, procurement, and disposal-related carbon costs. At the individual level, researchers have contributed to estimating the carbon associated with specific resources (e.g., Montoro *et al.*, 2023) and domain-specific practices (e.g., Grealey *et al.*, 2022). At the institutional level, organisations across the world have devised practices and reported on the carbon footprint of sectors including healthcare (Purohit, Smith and Hibble, 2021; Robinson *et al.*, 2023; Maida *et al.*, 2024) agriculture (Mazzetto, Falconer and Ledgard, 2022; Ozlu *et al.*, 2022), and industrial manufacturing (Panagiotopoulou, Stavropoulos and Chryssolouris, 2022). Individual-led action in computation (Lannelongue, Grealey and Inouye, 2021), and clinical sciences (Farley and Nicolet, 2023) has demonstrated the power of researchers in generating carbon footprint data from a variety of specialised domains. Such actions have supported collective action by researchers to design accredited sustainable waste disposal initiatives (e.g., LEAF and MyGreenLab) (Schell and Bruns, 2024). However, decentralised efforts are in their infancy in many disciplines especially beyond clinical medicine and agriculture, with partial reporting on equipment and techniques alongside methodological inconsistency hampering effective carbon footprint estimation and weakening cohesive and coherent mitigation strategies (Rae *et al.*, 2022; Robinson *et al.*, 2023).

Scientific research is one domain of the carbon economy that has been underexplored and may come to increasingly dominate the landscape of energy usage in the coming decades. In particular, as science progresses, the complexity of the problems we address rises. The advancement in high-energy experimental techniques, the exponential rise of, and dependency on, artificial intelligence in analytical pipelines, and the increasing accessibility of science throughout the world means the carbon burden generated by science will continue to rise as we approach our climate targets (Budennyy *et al.*, 2022; Tamburrini, 2022). Understanding the current carbon footprint of science is hampered by partial reporting with major gaps in our awareness of costs across the life cycle of research (i.e., procurement, techniques, disposal). While scientific institutions are all directed to the same goal of knowledge creation, the different methodologies for scientific research - specialisation of equipment, techniques and protocols, recycling methods, mitigation strategies - can vary significantly. Consistent internal assessments of carbon footprints by researchers worldwide could provide an efficient, sustainable path to building an accessible data set and attentive accountants of discipline-specific carbon footprints, to focus and improve institutional, governmental, and industry decarbonisation efforts.

There are many methods for estimating carbon footprints, with varying complexity, which can make individuals and institutions reluctant to engage in carbon accounting (Fenner *et al.*, 2018; Robinson *et al.*, 2018). One solution is to create a cross-discipline community utilising the same methodologies to consistently report research-specific carbon footprints. To enable this, we propose a framework to quantify emissions emerging from individual PhD theses. We hope that these quantifications can contribute to data on, and serve as interim proxies for, the emissions of multiple disciplines and institutions. There were 115,705 PhD students studying in the UK in 2022/4 (HESA, 2024), with an estimated 277,700 doctorates awarded annually worldwide (OECD, 2019) Many of these students will become part of the next generation of academics and public servants; thus, engaging doctoral students with carbon accounting could help strengthen commitment to sustainability within academia and industry while generating a large volume of reliable data for effective and accountable carbon mitigation strategies. Furthermore, each student generates a thesis which can serve as a common vehicle for disseminating information about the carbon footprints of specific research activities.

Here, we demonstrate how PhD students can consistently measure the carbon footprint of their work, using one doctoral student's research in a neuroscience *Drosophila* lab as our case study. We present the carbon costs associated with each stage of the research life cycle, from procurement through to experiments, analysis, data storage and material disposal. As part of this life-cycle assessment, we calculate estimates of the carbon cost associated with many activities relevant to other neuroscience and *Drosophila* labs, including scope 1 emissions from anaesthetisation of flies; scope 2 emissions from food preparation, commonly used experimental equipment and analytical pipelines, and waste disposal; and scope 3 emissions associated with fly requisitions from stock centers. Additionally, we calculate the total carbon cost associated with one year of PhD work in neurophysiology (including research and travel), using robust, easily replicable methodologies. Finally, we explore reported variations in the equivalent carbon dioxide emissions (CO_2e) associated with UK National Grid energy to better understand the role of geography and time in the production of scope 2 emissions from research. Overall, we demonstrate how PhD students and other researchers can begin to account for the carbon costs of their work and discuss how uptake of this approach could improve research sustainability by informing targeted emissions mitigation strategies.

Results

The Carbon Cost of *Drosophila* Neuroscience Research

Reliable carbon accounting in academic research is vital for tailoring effective mitigation strategies and generating a continuous stream of robust data to hold implementation policies accountable.

Drosophila neuroscience research generates scope 1 (direct), 2 (indirect via electricity production), and 3 (incorporating all other life cycle emissions not operated or controlled by the user) carbon emissions. Over the course of one year, we conducted life cycle analyses that accounted for the carbon generated by all stages of one PhD student's (the first listed author's) research activities, assuming all energy came from the mains network grid in Southern Scotland. Here, we detail the measured and estimated carbon dioxide equivalent emissions (CO_2e) for each stage of the research life cycle in a chronological manner commencing with food generation and finishing with material disposal and data storage (Figure 1A). We describe how we quantify carbon emissions from all stages of the research cycle. A summary of this quantification is provided in Figures 1B and 1C.

Food generation

All animal research depends on food generation. This often relies on in-house equipment, which generates scope 2 carbon emissions via electricity consumption. For *Drosophila*, food sources consist of a ready-made cornmeal-based resource which is rehydrated, heated and mixed (Lakovaara, 1969) Flies are raised on this medium in vials, with a new generation of flies transferred to fresh vials each month to maintain the genetic stock. In our laboratory, 216 stocks are maintained, and additional vials are used to rear flies for crosses and experiments. Every month, these activities for our research group consumed a combined 700 medium-sized vials with an average of 10g of yeast extract food per vial. The individual PhD student in this study used on average 52 vials per month, amounting to 7.4% of the total laboratory consumption (see Methods). In common with many laboratories, large batches of food are supplied across multiple research groups. Consequently, technicians rely on large-scale, high-power equipment whose energy supply is not easily accessible. Modern research kitchen equipment often incorporates digital monitoring of energy consumption. However, in our case, the use of older equipment precluded direct determination of energy usage, for safety reasons. Thus, we accounted for the maximum electrical power required for food generation based on manufacturer reporting. For heating and mixing of food, we found a maximum power usage of 7.536 kWh (Table 1). We estimated the associated greenhouse gas emissions from electricity generation using region- and time-specific kWh-to-CO_2e conversion factors. The kWh-to-CO_2e conversion factor varies across time and space due to changes in the balance of power derived from different types of power sources (Raugei, Kamran and Hutchinson, 2020) contributing dynamically to the UK National Grid. To find kWh-to-CO2 conversion factors for Southern Scotland, we used the Carbon Intensity API, a free resource that provides region-specific information on the carbon intensity of UK National Grid energy based on machine-learning forecasting (api.carbonintensity.org.uk). Using estimates of monthly average conversion factors (see Methods), we found that food generation for the whole research group emits

on average 152.4 g CO_2e per month, which, given monthly variations, totalled 3.2 kg CO_2e for the June 2023 - May 2024 period. Given that our individual PhD student utilised 7.4% of total monthly vials, food generation for this single PhD student's work emits on average 11.3 g CO2e per month (Figure 1B), which, given monthly variations, totalled 237.8 g CO2e (Figure 1C) for the June 2023 - May 2024 period.

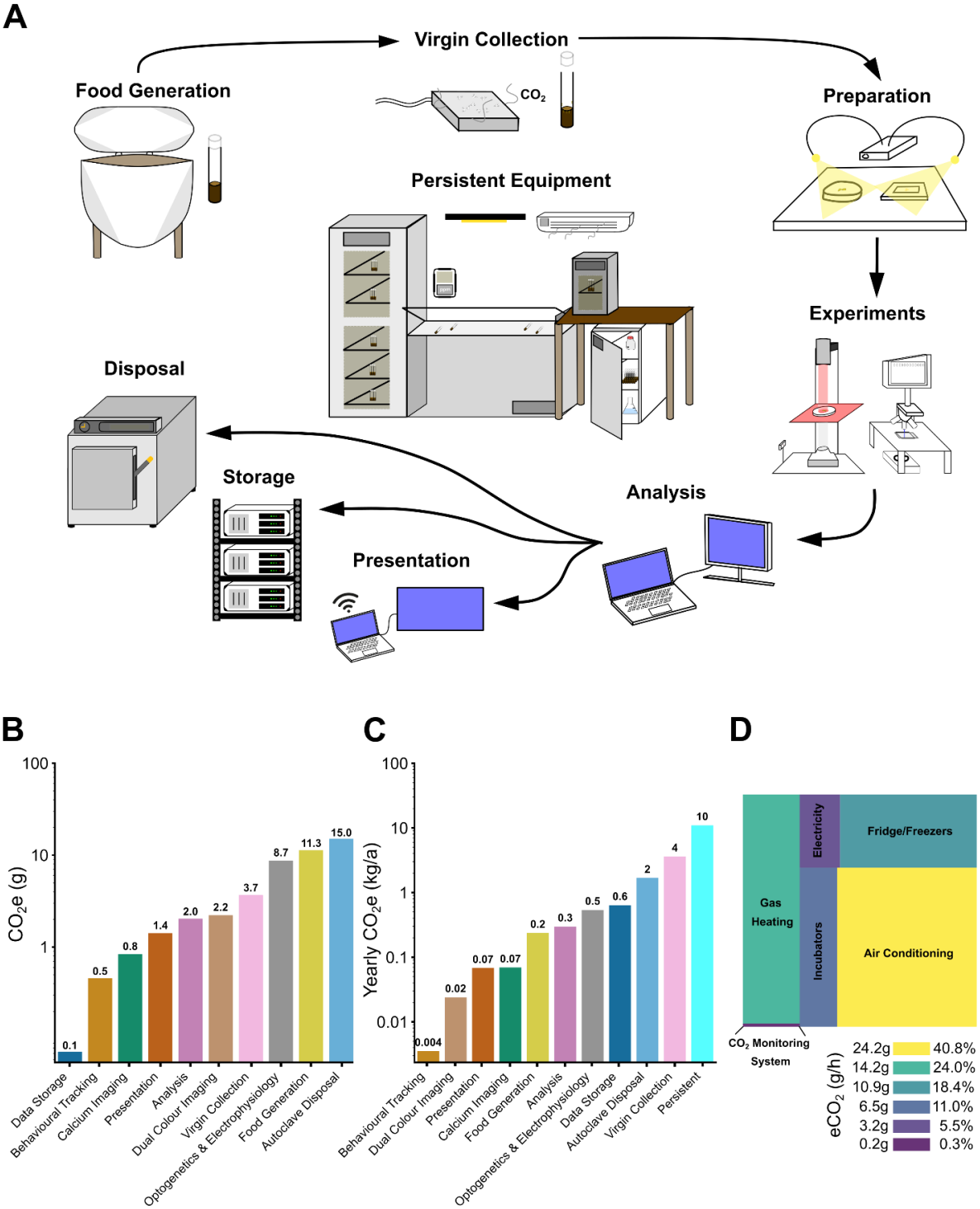

Figure 1: The carbon costs associated with one year of *Drosophila* neuroscience research.

(**A**) The life cycle of *Drosophila* experimental research. (**B**) Equivalent carbon dioxide emissions, CO_2e (g), per experimental preparation (behavioural optogenetics, calcium imaging, electrophysiology), per preparation (analysis), per vial (virgin collection), and per 700 medium-size vials (food generation, disposal), to 1 d.p. (**C**) Yearly equivalent carbon dioxide emissions CO_2e (kg/a) generated from the work of one researcher in South Scotland for June 2023 - May 2024 including all aspects of the research lifecycle based on total number of experiments completed, vials used, and data generated per month. (D) The average hourly equivalent carbon dioxide emission rate, CO_2e (g/h), calculated from the power drawn by different persistent laboratory equipment and the average monthly kWh-to-CO_2e conversion factor for Southern Scotland.

Drosophila genetic engineering (virgin collection)

Drosophila are commonly used model organisms in neuroscience due to ease of genetic manipulations involving selective breeding between transgenic lines. A vital part of this process is anaesthetisation of flies with CO_2 before sorting newly-eclosed female virgins for genetic crosses, resulting in scope 1 carbon emissions. Anaesthetisation involves the variable use of a CO_2 gun (up to 2s per vial) and pad (up to 10s per vial). Using a gas syringe and gas displacement method (see Methods), we accounted for the direct release of 3.7g CO_2 per vial of sorted flies (up to 0.2ml CO_2). Considering the vast number of laboratories dedicated to *Drosophila* genetics, the level of direct release of CO_2 from anaesthetisation is likely large but currently unknown. For one PhD student, we calculated a total of 3.6 kg CO_2e release (from 972 vials) from virgin collection per year (Table 2). However, *Drosophila* labs that rely more heavily on screening genetics (i.e., involving several, consistently used multi-stage genetic crosses like in developmental-based *Drosophila* research) could conservatively directly release <16.7kg CO_2e (~4500 vials) a year per researcher (see Methods). Virgin collection often relies upon a microscope with LED illumination to aid in sex determining the adult *Drosophila*.

Preparation and experiments

Next, we wanted to understand how energy use during experimental work contributes to scope-2 carbon emissions. To estimate the carbon intensity of different experiments throughout the year, we used power meters to measure the power drawn by electrical apparatus during experiments, and applied monthly average kWh-to-CO_2e conversion factors calculated from Carbon Intensity API (api.carbonintensity.org.uk) data for the period June 2023 to May 2024.

Experiments involving optogenetics, calcium imaging, and electrophysiology are staples of modern research especially in neuroscience (Knot *et al.*, 2005; Scanziani and Häusser, 2009; Häusser, 2014). All of these experiments utilise high-powered LED lights, high-frame rate (100 frames per second), supercooled (-70 °C) cameras, and persistent signal processing units. In our work, we used these

experimental techniques to monitor the motor activity in isolated *Drosophila* neural tissue using genetically encoded calcium indicators and motor root bursting patterns. In the case of electrophysiology and optogenetics, we used pulses of LED-generated light to induce changes in neural network activity, which we measured with continuously-recording electrodes. For dual-colour calcium imaging, we utilised a spinning-disc confocal microscope to acquire images of neurons simultaneously expressing two different genetically encoded fluorescent calcium indicators.

All imaging and optogenetics experiments were performed on isolated neural tissue immersed in physiological saline and dissected under a dissecting microscope fitted with LEDs. Physiological saline (Baines External Saline, (Marley and Baines, 2011)) required the use of deionisation and filtration equipment that yielded 5.27 g CO_2e for every 4 L of saline produced. Over the 2023-4 research year, saline generation accounted for 26.37 g CO_2e (20 L). Our microscope's LEDs yielded, on average, 0.03 g CO_2e every preparation (up to 10 minutes per prep) amounting to a precursory amount of 4.07 g CO_2e for all experimental work (151 preparations). Overall, for dissection alone, we calculated an average annual carbon intensity of 30.44 g CO_2e (Table 2). Preparation time was directly factored into each experimental estimation.

Based on the average kWh-to-CO_2e conversion factor for 2023-4, we found the average CO_2e emissions per preparation for each technique (without preparation): behavioural optogenetics (0.5 g); calcium imaging (0.8 g); dual-colour calcium imaging (2.2 g); and optogenetics and electrophysiology (8.7 g) (Figure 1B). Over the course of the year June 2023 - May 2024, we recorded the quantity (151 experiments) and duration (154.5 hours) of all experimental work performed by one PhD student (Table 2). Again, using monthly average kWh-to-CO2e conversion factors, we found that these experiments produced a total of 0.64kg CO_2e annually (Figure 1C).

Data analysis, storage, and presentation

Next, we evaluated the emissions associated with data analysis, storage, and presentation.

Analysis requires computationally demanding and time-intensive processing pipelines. Within a year, the neuroscience PhD student utilised several different CPU-based analytical pipelines to visualise and interpret recorded data. For calcium imaging, image sequences required positional stabilisation over time, extraction and visualisation of fluorescence changes in regions of interest, and relational analysis across many regions of interest. For electrophysiology, nerve root bursting signals require pre-processing rectification and smoothing followed by extracting signal relationships and quantities like bursting duration. For behavioural tracking, videos are analysed using trained neural networks through the software TrackMate (Tinevez *et al.*, 2017) and DeepLabCut (Mathis *et al.*, 2018) to extract

positional and velocity information over time. For the 2023-4 research year, calcium imaging and electrophysiology were the only analytical pipelines utilised. All analysis required extraction and post-processing with programs like DataView (Heitler, 2007) and custom-built Python scripts. Through tracking the hourly power usage on a laptop during five instances of post-hoc analysis (i.e., pre-processing in a signal processing software using DataView, post-processing and visualisation in Python3), we accounted for an average of 2.0g CO_2e per preparation, yielding 302g CO_2e across the year.

All of the data collected were stored within a university-based secured remote server (PureSANs array) with power diagnostics reported weekly from the server provider. The combined power consumption of the server's production and total flash disk storage was 34 MWh/year. We estimated the data storage energy cost based on the proportion of our laboratory's data share size (27.39 TB, 2.3% of total server space (1228.8TB)) to be 19 kWh/TB/year which equated to 512 kWh/year. Based on the South Scotland kWh-to-CO_2e conversion factor (20 g CO_2e/kWh, Figure 2B), the emissions burden of the laboratory's data storage amounted to 1.2g CO_2e per hour or 10.35 kg CO_2e for the 2023-4 research year. A single year of PhD research generated 1.69TB of data (i.e., raw video files, extracted csv files, python scripts, figures, manuscripts), equivalent to 6.2% of the laboratory's total data storage space. Thus, the emissions burden of data storage for a single South Scotland PhD student amounted to 0.07g CO_2e per hour (Figure 1B) or 637.7g CO_2e for the 2023-4 research year (Figure 1C).

Beyond analysis and storage, data is often communicated, shared, and presented through video streaming applications (i.e., Microsoft Teams) to supervisors, academic staff, and wider academic circles. We found 0.07 kWh was used by our laptop model (Table 1) per 1-hour online meeting where visual and audio material was shared continuously amounting to, on average, 1.42g CO_2e per instance (Figure 1B). Given our recorded average of four online contact hours per month, we accounted for 68g CO_2e for the 2023-4 researched year (Figure 1C).

Overall, data storage, analysis, and online presentations produced 1 kg CO_2e for the 2023-4 research year (1.6x the yearly CO_2e generated from all recorded experimental work).

Disposal

Frontier biological research using genetically modified organisms often requires extensive use of energetically expensive sterilisation and disposal mechanisms, thereby incurring a high indirect energy-related (i.e. scope 2) carbon cost. At the end-stage of the *Drosophila* research life cycle (Figure 1A), high-temperature, high-pressure autoclaves are used to sterilise vials, glassware containing chemical modulatory compounds, and equipment that has contacted genetically modified material.

We accounted for the 10-kWh maximum power usage specified by the manufacturer (Table 1), resulting in a maximum average of 202.2g CO_2e per month for the total laboratory requirement of 700 vials. We found that autoclaving produced a total of 22.7kg CO_2e for the June 2023 - May 2024 period for the entire laboratory. For a single PhD student (7.4% of total load), autoclave disposal of vials amounted to 15.0g CO_2e per month (Figure 1B) and a total of 1.7kg CO_2e (Figure 1C) for the June 2023 - May 2024 period.

Persistent equipment

Accompanying the experimental life cycle, equipment for climate control (e.g. air conditioning and incubators) is an essential feature of research facilities. Within our 82.52 m^2 research space, gas-based heating systems and national grid-supplied electricity for lights were used alongside air conditioning units, incubators, CO_2 monitoring systems, and fridge/freezer units (Table 1, Figure 1D). The University of St Andrews uses SystemLink™ to dynamically track kWh used for heating and lighting per floor area per building (see Methods). Using SystemLink™ information, we found building maintenance (e.g., heating, lighting) accounted for 36% of total persistent equipment emissions. Surprisingly, incubators accounted for only 5.5% of total persistent equipment CO_2e emissions, producing on average ~3.2g eCO_2 an hour. The persistent CO_2 monitoring systems yielded an average of 0.2g eCO_2 an hour. Overall, persistent equipment accounted for the largest proportion of CO_2e generated per year in our laboratories (212 kg CO_2e, Figure 1C).

Taken together, one year of *Drosophila* cellular neuroscience research conducted by a PhD student in South Scotland 2023-4 produced 18.15 kg CO_2e. In particular, across the research life cycle, direct research-related activities generated 3.62 kg scope 1 (i.e., direct release by virgin collection and gas-related heating), 13.84 kg scope 2 (i.e., food generation, experimental work, analytical pipelines, and resource disposal), and 0.71 kg scope 3 (i.e., data storage, distribution, and presentation) CO_2e emission costs.

Associated Travel Costs for a Researcher

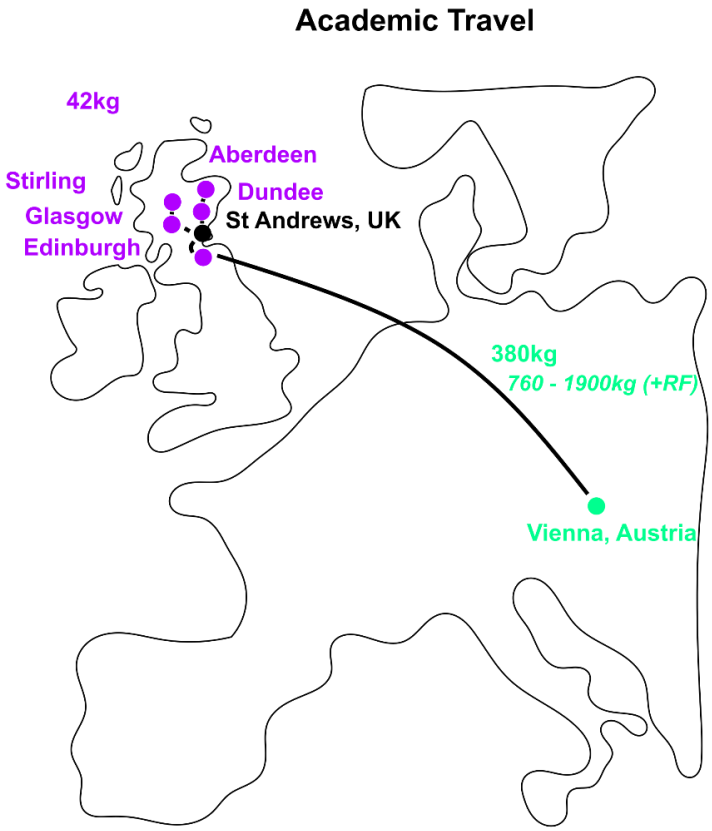

Figure 2: eCO_2 released via public travel for a PhD researcher 2023-4.

Representation of the accrued travel costs of an individual PhD researcher throughout Scotland via national rail (purple) and economy air travel (cyan) without and with (*below*) radiative forcing index factors.

Aside from conducting research, researchers require travel for training, public engagement, and collaboration. We accounted for the travel-associated carbon emissions for the neuroscience PhD student to provide a case study for non-research related carbon costs of academia (Figure 2). We used ICAO (ICAO, 2024), a free resource for estimating the carbon intensity of travel. ICAO bases carbon emissions measurements exclusively on flight distance, cargo type, plane model, and logged fuel usage per passenger weight. However, it does not include radiative forcing (RF) factors which encapsulate the indirect effects of greenhouse gas emissions caused by contrail formation at higher altitudes during flight (Fuglestvedt *et al.*, 2003; Lee *et al.*, 2021).

In our case study, travel occurred both internationally via air and locally by rail. Train travel to local Scottish universities for mandatory PhD-related training and research presentation events generated 42 kg CO_2e (Table 3). Air and associated intermediary travel to the Federation of European Neuroscience (FENS) 2024 conference in Vienna yielded 380 kg CO_2e (Table 2). Using the

comprehensive RF estimation range (1.0 - 4.0) made by Lee et al., (2019), we found that RF may have increased the yearly air travel carbon cost to 760-1900 kg CO_2e. Thus, the indirect cost of PhD research related to travel amounted to 442 kg CO_2e (without RF) or 802-1942 kg CO_2e (with RF) scope 3 emissions. For comparison, the total CO_2e emissions associated with nine travel instances (without RF) was equivalent to ~191% of total experiment-related emissions (422 kg versus 2.21 kg) for the 2023-4 research year. In other words, the total travel-related yearly emissions (without RF) were equivalent to the average emissions yield of ~32 electrophysiology experiments, ~124 dual colour calcium imaging experiments, ~334 calcium imaging or ~618 behavioural optogenetics experiments conducted in South Scotland.

Known Unknowns: The International Cost of *Drosophila* Science

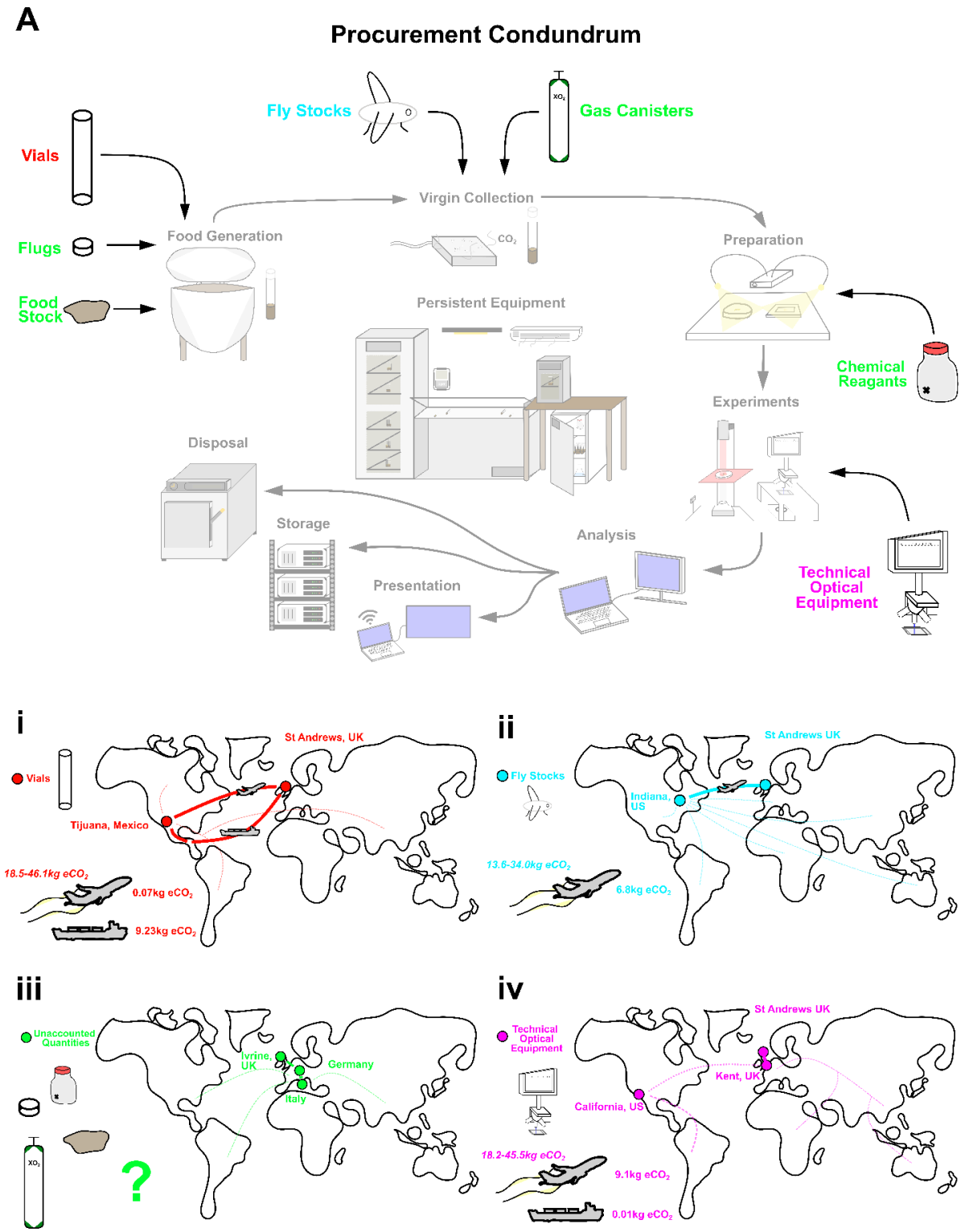

Figure 3: Scope 3 Procurement Emission Estimations for *Drosophila* Biological Research

(**A**) Aside from emissions produced by experimental research and persistent equipment, additional resources also have associated greenhouse emissions at the main stages of research: (**i**) *Drosophila* vial resources are sourced (500 per order) from Mexico through Scientific Laboratory Supplies™, (**ii**) *Drosophila* stocks are mainly

sourced from Bloomington Indiana, US with estimate quoted per vial, (**iii**) unaccounted procurement resources: chemical reagents are mainly sourced from Sigma™ with many transport centres across Europe, gas canisters are sourced from BOC™ with Fife-based distributors, flugs and food resources have unknown origin sites (**iv**) optical equipment from CAIRN Research Ltd™ (Kent, UK) or Chroma™ (Irvine, California, US) with one of our orders consisting of four filters and one mirror. Solid lines represent parts of the transport link with eCO_2 estimates. Dotted lines represent expected but unquantified parts of the transport procurement links upstream in the procurement chain. Radiative factor (1.0 - 4.0) air-travel cost estimates are quoted behind plane images in each panel in italics.

Aside from producing direct emissions (scope 1) or indirect by electricity-based experimental work and building maintenance (scope 2), equipment procurement by laboratories significantly contributes to international emissions (scope 3). Here, we focused on some ubiquitous resources for *Drosophila* research (Figure 3A) and tried to account for their indirect emissions. However, as noted previously (Achten, Almeida and Muys, 2013), companies often reject information requests by deeming transportation routes, times, energy mixtures in manufacturing, and cost as proprietary information. Nevertheless, some information (e.g., manufacture origin, energy mixture in manufacturing, transportation routes) was provided and is sufficient to produce a robust estimate when combined with UK GOV Emission Conversion Data (see Methods).

First, we attempted to estimate the cost of sourcing plastic vials for our representative PhD project. Through liaison with Scientific Laboratory Supplies™, we discovered that their basic non-recyclable plastic vials (widely used by *Drosophila* researchers) were sourced from Tijuana, Mexico. However, we were unable to ascertain the exact method of delivery from Mexico to the UK. Thus, we instead used best approximations for distance yielded by using Google's Distance Matrix, mode of transport assumptions, and UK GOV 2024 conversion factors for CO_2e for mode of transport (see Methods). If delivery uses high-carbon, faster transport (e.g., air travel with short-distance HGV transfers) we estimated an upper value of 9.23kg CO_2e per 500 vials for transportation from Tijuana, Mexico to Edinburgh Airport towards the St Andrews, UK. If we incorporate RF estimates (Fuglestvedt *et al.*, 2003; Lee *et al.*, 2021), air-based procurement of fly vials rises to 18.46 - 46.15kg CO_2e per 500 vials. However, if delivery uses low-carbon, slower transport (e.g., bulk HGV from Tijuana to Mexico City (Benito Juarez, cargo shipping to London, UK) we estimate a potential 132x reduction in CO_2e (70g) (Figure 3Ai, Table 4). Given a single PhD student used 624 vials (June 2023 - May 2024), vial acquisition contributed 18.46kg CO_2e (36.92 - 92.30 kg CO_2e with RF) if using flight-based procurement or 0.14kg CO_2e if using cargo-based procurement. For the laboratory as a whole, we acquired 8500 vials in the 2023-4 research period amounting to 156.96kg CO_2e (313.92 - 784.80 kg CO_2e with RF) if using flight-based procurement or 1.25kg CO_2e if using cargo-based procurement.

In addition to vials, *Drosophila* research often relies on importing flies from Bloomington Indiana, US, or alternative stock centers. The time-sensitive nature of transporting live flies necessitates air freight. By using UK GOV 2024 conversion data and Google Matrix's distance estimations between origin site and final destination, we estimated a production of 6.79 kg CO_2e (without RF) per vial ordered to St Andrews, UK, generated by cargo flight from Indiana International Airport to Edinburgh Airport followed by HGV travel to St Andrews, UK (Figure 3Aii, Table 4). Incorporating RF, fly procurement may be 13.56 - 33.97kg CO_2e. Importantly, we could not estimate upstream carbon emissions from research institutions donating *Drosophila* stock to the Indiana-based store nor the precise upkeep costs (though estimates made by this paper could be cross-applied to resources at Bloomingtons at a future date) so the total life-cycle scope 3 cost for *Drosophila* procurement will be larger. Nevertheless, a single PhD student ordered 48 new *Drosophila* stocks from Bloomington's amounting to 81.48 kg CO_2e (162.96 - 407.40 kg CO_2e with RF) for the June 2023 - May 2024 period.

Our research utilised optical equipment that we often continuously source from suppliers like CAIRN Research Ltd™ and producers like Chroma™. While we were unable to acquire information about production and distribution costs from the producers of our cameras, filters, and lenses, CAIRN Research™ did release information about distribution centres and modes of delivery for our 2023-4 items (4 filters, 1 mirror, 0.08kg, Table 4). Our optical orders were sourced from the CAIRN Research Ltd™ facility in Kent, UK by HGV to St Andrews, UK. CAIRN Research Ltd™ procures the optical equipment from the manufacturer intermediate Chroma™ in California, US. Similar to our methodology for vial procurement estimation, we used publicly available cargo route information and UK GOV 2024 conversion factors to estimate low (HGV, cargo ship: 0.01kg CO_2e per order) and high (HGV, cargo flight from John Wayne to Edinburgh Airport: 9.11kg CO_2e per order) carbon load procurement routes (Figure 3 Aiv). Incorporating RF, optical procurement may be 15.90 - 43.22kg CO_2e.

In contrast to our estimations of vial, optical equipment and fly stocks, the lack of publicly available data in chemical reagent supplication (Sigma-Aldrich™, Avantor™ by VMR™, Thermo Fisher Scientific™), gas canister supply (BOC™), or yeast food made any reasonable carbon estimates from those lab dependencies unfruitful. In all, we were unable to discover the prior transportation routes, pre-supplies, or locations of precursor materials earlier in the supply route from any of our chemical suppliers (Figure 3iii). However, we did note down our yearly usage of these materials for future estimation as information becomes more publicly available (Table 5).

Overall, total equipment procurement for the 2023-4 year for a single PhD student equated to 81.63 - 542.92kg CO_2e scope 3 emissions cost. In effect, the median year's procurement-related emissions

(230.65kg CO_2e) were equivalent to 363x of the total experiment-related emission cost. Altogether, laboratory persistent operations, experimental load, individual academic-related travel, and procurement totalled at < 2502 kg CO_2e for the 2023-4 year.

Research Costs Across Space and Time

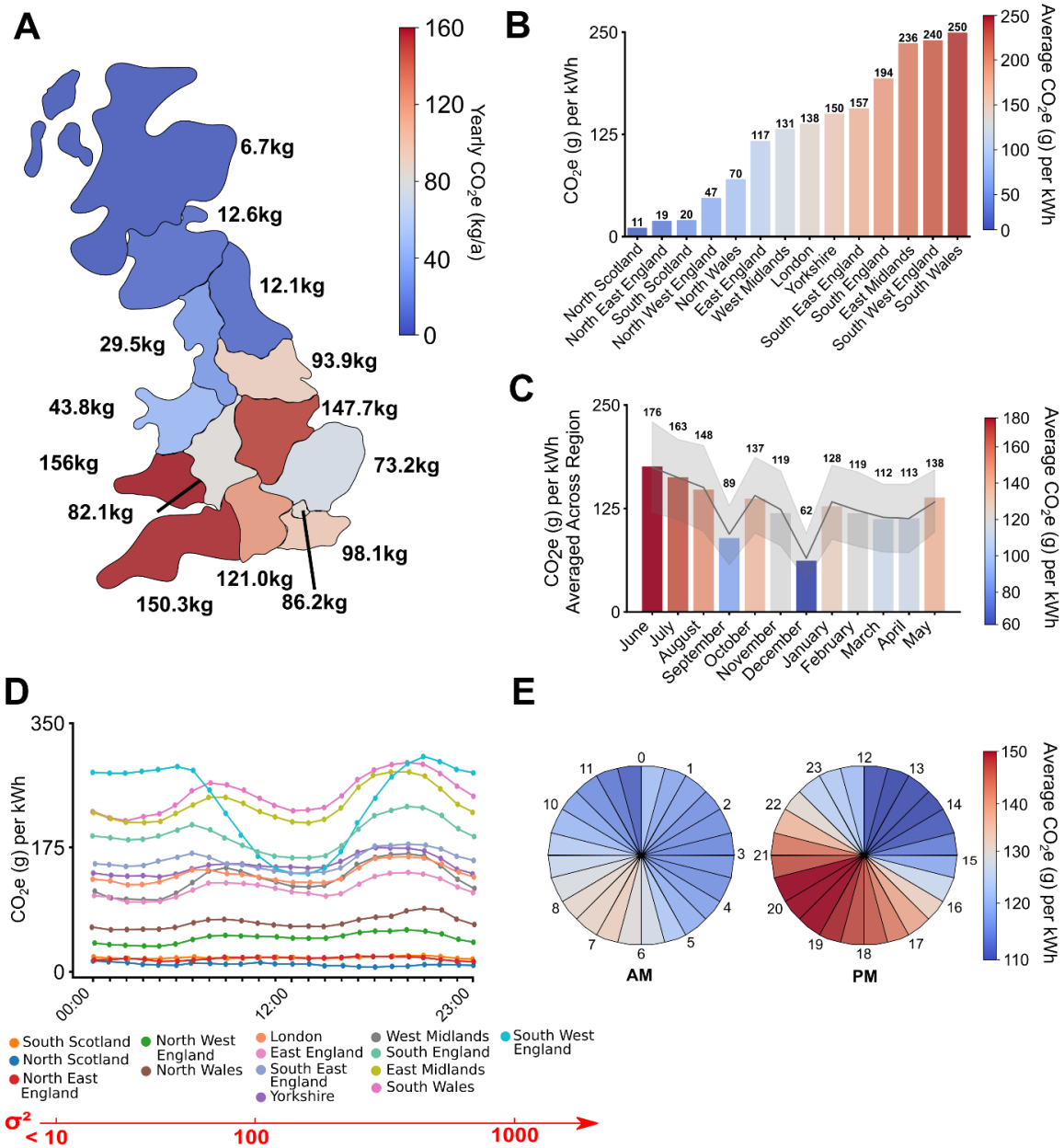

Figure 4: The carbon cost of research by region, month, and time of day in 2023-4.

(**A**) The yearly carbon costs of one researcher and total laboratory costs (total 700 vials per month) in different regions of the UK. (**B**) The average CO_2e-per-kWh generated from each region of the UK from June 2023 - May 2024. (**C**) The monthly CO_2e-per-kWh averaged across all regions from June 2023 - May 2024 as recorded by the UK National Grid. The grey line represents the average trend across all regions of the UK while the shaded grey region shows the standard error. (**D**) Variation in the average CO_2e-per-kWh for different UK regions with time

of day, with ranked variance of the regions listed below the time series plot. (**E**) The average CO_2e-per-kWh for each 30-minute segment on average across regions and months in the UK from June 2023 - May 2024 as recorded by the UK National Grid.

The carbon intensity of research varies widely depending on the geographical region where it is conducted, largely due to differing energy mixtures across different portions of the UK electricity grid (Figure 4A-B, see Methods). Between June 2023 and May 2024, we estimated that persistent equipment and experimental work together produced 12.6 kg CO_2e from mains electricity in South Scotland. Applying different regional kWh-to-CO_2e conversion factors to the total energy consumed by persistent equipment and experimental work yields large differences in estimated CO_2e emissions. For instance, conducting our research within North Scotland (e.g., Aberdeen) could have reduced total CO_2e emissions by a factor of 1.87 (to 6.7 kg CO_2e). In contrast, had our research consumed electricity supplied to South Wales, we would have released 12.3x more CO_2e (156 kg CO_2e) than we produced in South Scotland. The largest difference is between North Scotland and South Wales, with on average 23.1x more CO_2e emissions in South Wales compared to North Scotland.

Aside from geography, the month and time that experiments are conducted also affects carbon emissions. For instance, an electrophysiology dataset (N = 10 preparations, 2 hours per prep) collected in South Scotland in December may produce 265 g CO_2e whereas generating the same dataset in June could result in 2.8x higher carbon emissions (750 g CO_2e) (Figure 4C).

Similarly, performing experiments at different times of day results in large variations in CO_2e (Figure 2D, E). For example, performing a dual-colour calcium imaging experiment (1 hour) at 13:00 may produce 11.3 g CO_2e whereas conducting the same experiment at 19:00 produces on average 36% more CO_2e (15.5 g). However, temporal variation in CO_2e-per-kWh is greater in some regions (e.g., Southwest England, σ^2 = 3505.2 g CO_2e per kWh) than others (e.g., South Scotland, σ^2 = 1.9 g CO_2e per kWh), largely due to differing proportions of renewable resources in regional energy mixtures.

Discussion

Here, we present the direct and indirect carbon costs of conducting one year of high-intensity, frontier *Drosophila* research using widely used imaging techniques and methods for a single neuroscience PhD student. We show the equivalent carbon emissions (CO_2e) associated with a variety of biological techniques widely used beyond the field of *Drosophila* research. Alongside scope 1 costs associated with genetic construction, we provide estimates for scope 2 and 3 costs related to research including travel, procurement, and climate control system costs at both the laboratory and individual PhD student level. Additionally, we raise the importance of geography and time when conducting research

supplied by national grids that have region-specific resource mixtures (i.e., varying levels of renewable vs non-renewable resources) and varying peaks in energy demand. With variation in mind, we show how the Carbon Intensity API can be used to create region- and time-specific estimations of researchers' carbon footprints that are more accurate than estimates obtained exclusively using government-reported kwh-to-CO_2e conversion rates. Such a life cycle assessment exemplifies how doctoral students can make carbon estimations about their research, aiding in the availability of open-access emissions data from the research sector.

Using "cradle-to-grave" life-cycle assessments, the medical and clinical sciences have taken great strides in carbon accounting (e.g., Robinson *et al.*, 2018; Maida *et al.*, 2024). However, the limited number of individual estimates, inconsistent methodology, and partial attempts at capturing complete life-cycles signals the necessity of increased participation in carbon accounting and consistency in how emissions estimates are calculated (McGain and Naylor, 2014; Purohit, Smith and Hibble, 2021; Valls-Val and Bovea, 2021; Robinson *et al.*, 2023). The imminence of key climate targets necessitates efficient individual, collective, and institutional action to mitigate carbon emissions across all sectors. We believe that accurate and publicly available emissions data will be necessary to inform those actions. While a complete dynamic picture of the emissions landscape may be elusive, even a modest increase in emissions data could be readily used to limit and validate large-scale carbon footprint models across disciplines, helping to inform public policy (Ni *et al.*, 2018). We suggest that the current paucity of estimations can be partially remedied by engaging researchers at all levels of career progression: a series of individual-led estimation efforts will, together with accurate and consistent carbon emissions estimates, help to capture complete research life cycles even if some researchers can individually account for the carbon produced only by specific life-cycle elements.

The medical and clinical sciences have taken great strides in carbon accounting. Primarily through life-cycle ("cradle-to-grave") assessments , we now possess both direct and indirect emission estimates for surgical operations (Robinson *et al.*, 2023), endoscopy (Maida *et al.*, 2024), anaesthesia (McGain *et al.*, 2020) medical care infrastructure (McGain and Naylor, 2014), and patient travel (Purohit, Smith and Hibble, 2021). These wide ranging carbon emissions estimates have informed research into effective carbon mitigation strategies at multiple levels of medicine (Montoro *et al.*, 2023; Quann *et al.*, 2023).

However, the limited number of individual estimates, inconsistent methodology, and partial attempts at capturing complete life-cycles signals the necessity of higher engagement in carbon accounting and consistency in how emissions estimates are calculated (McGain and Naylor, 2014; Purohit, Smith and

Hibble, 2021; Valls-Val and Bovea, 2021; Robinson *et al.*, 2023). Additionally, multi-sector data could be readily used to limit and validate large-scale carbon footprint models across disciplines (Ni *et al.*, 2018). We suggest that the paucity of individual estimations can be partially remedied by engaging researchers at all levels of career progression: a series of individual-led estimation efforts will, together with accurate and consistent carbon emissions estimates, help capture complete research life cycles even if some researchers can only account for the carbon produced by specific life-cycle elements during their research.

Indeed, our emerging understanding of several disciplines' carbon footprints is often built upon a grassroots approach whereby individual researchers and laboratories contribute their carbon footprint and employ ex-ante and post-hoc mitigation strategies to help the community, for example in astronomy (Martin *et al.*, 2022), particle physics (Janot and Blondel, 2022), medical imaging (Picano, 2021), and high-performance computing (Lannelongue, Grealey and Inouye, 2021). Scientists have used these procedural insights to build accreditation programs, such as MyGreenLab, LEAF that seek to inform and reward researchers' efforts to adopt sustainable research practices (Freese *et al.*, 2024).

While work has begun to account for carbon produced by medical neuroimaging (i.e., fMRI) (Souter *et al.*, 2023, 2024), to our knowledge, our work is the first to account for cellular neuroscience imaging and *Drosophila*-related research using real-time regional emissions estimates. Thus, our work, methods, and data are intended to plant the seed for further carbon accounting by other disciplines of neuroscience and STEM, across institutions and geographies. Importantly, we envisage PhD-level, individual-driven, lab-focused carbon accounting building on attempts to accurately carbon footprint higher-education institutions (e.g., Valls-Val and Bovea, 2021), to generate an actionable foundation for institutional and government policy for our domain of STEM.

Methods of Carbon Accounting

Differences in the methods authors use to account for carbon emissions have produced a large variability in estimates (Pandey, Agrawal and Pandey, 2011). Naturally, there are sensible justifications for adopting coarse estimates when more precise estimations (e.g., equipment-specific energy consumption and regional electricity carbon intensity) are unavailable. Complementing Souter *et al* (2023) carbon estimation approach which tracks mains electricity-related emissions using Electricity Maps (https://app.electricitymaps.com/map), we utilised the National Grid-based Carbon Intensity API (https://carbon-intensity.github.io/api-definitions/#carbon-intensity-api-v2-0-0) to demonstrate a more precise method of carbon accounting. However, at the time of writing, region-specific data was restricted to only a few areas (e.g., UK counties and some US states). As climate targets near and

international pressure mounts, we predict that demand for APIs like Carbon Intensity will increase, and hope that members of the community will advocate for local governments and private providers to publicise energy-generation mixes so developers can satisfy the need for regional precision in carbon accounting. Focusing on regional precision can enable the research community, including future doctoral students, to disentangle the sources of variability in carbon footprint estimates and thus be better able to formulate effective mitigation strategies.

Mitigation Strategies

Carbon mitigation is achieved by pre-emptive strategies, which seek to avoid anticipated emissions, and sequestration strategies, which aim to capture the equivalent of previous and unavoidable emissions. Assessment of a carbon footprint is often paired with an equivalent sequestration comparative (Elli *et al.*, 2024). However, sufficient carbon sequestration is a complex demand with factors like tree species, the plantation ecosystem, climate change, biodiversity, and soil ecology all contributing to varying mitigation success (Woodward *et al.*, 2009; Abbas *et al.*, 2017; Vacek, Vacek and Cukor, 2023). In addition, the rise of business models around reforestation commonly incentivise short-term sequestration followed by biomass extraction which renders the mitigation strategy effectively redundant. Alternative sequestration methods (e.g., carbon-capture-storage) are often too expensive for individuals and university institutions to participate in the short term to reach 2030-50 climate targets, especially considering the financial trade-off made against more solvent renewable-led investment for emission mitigation (Sgouridis *et al.*, 2019). While post-release mitigation is necessary to combat decades of over release of greenhouse gases, the complementary, more robust and immediately accessible method of mitigation is pre-emptively reducing activity emissions and procurement demands, leaving sequestration efforts to capture historic and unavoidable emissions via large private and government-led initiatives. Like most human decisions, assessing and knowing the quantity associated with a harm or benefit can be an additive, sufficient motivating factor for action (Zhang *et al.*, 2019). For example, our work revealed unexpectedly high energy consumption by persistent climate control systems due to aging, inefficient equipment. This has motivated us to acquire more energy efficient equipment with effects we can quantify and report consistently in the future. Alongside persistent equipment, the amount of direct emissions generated by *Drosophila* sorting for genetic crosses far exceeded our expectations. Considering the wide usage of *Drosophila* due to their genetic versatility, the scale of CO_2 release by the *Drosophila* community will be considerable. According to FlyBase's Fly Lab list (https://wiki.flybase.org/wiki/FlyBase:Fly_Lab_List), there were 2,074 active Drosophila laboratories as of December 2024. Considering we estimated 4kg CO_2e per research, if we conservatively project an average *Drosophila* laboratory size of 3 researchers

per lab, this may amount to 25,000kg CO_2e per year which, according to ICAO's flight emission calculator, is equivalent to 40 return economy trips from Edinburgh to New York's JFK airport. Thus, we recommend that researchers investigate and invest in less carbon-intensive methods where appropriate, for *Drosophila* researchers this could take the form of anaesthetisation by cooling when powered by renewable resources. More broadly, by following the method and standards reported here, doctoral students in other scientific disciplines can expose other systemic, high-emission scientific practices, informing and motivating transitions to more sustainable methods.

Efforts to account for greenhouse gas emissions across disciplines have historically used non-regional, general kWh-to-CO_2e conversion rates that have contributed to wide variation in reported emissions. Here, we clearly demonstrate the impact of geography and time when calculating emissions estimates. The fact that changing our lab's location within the UK could increase our annual research carbon footprint by an order of magnitude raises questions about the best geographical location for high-energy research during the transition to 100% renewable energy. Importantly, large-scale relocation of high-energy research to a currently greener region would evidently create diminishing returns if energy supply and/or storage were inelastic. Notwithstanding, medium-term large-scale decarbonisation efforts of national grids could be complemented by short-term considerations of regional variation in energy mixtures when flexibility in the location of research or facilities exists.

While our calculations assumed electricity from the National Grid, many institutions have invested considerable effort into in-house generation of renewable, low emission energy (Adedeji, Akinlabi and Madushele, 2019; Vaziri, Rezaee and Monirian, 2020). This does, however, raise ethical questions concerning the link between financial privilege and the ability to invest in energy solutions: care must be taken to encourage creative, collaborative emissions mitigation strategies that are not restricted to select institutions. Indeed, even the production of low-emissions energy is not immediately net-neutral; emissions are expended in construction resources, maintaining infrastructure, and transport emissions aimed to provide "greener" in-house supply (e.g., from solar power: Wu *et al.*, 2021). Such ethical ramifications are analogous to treatment-versus-waste questions reported in medical carbon accounting (Thiel and Richie, 2022). While we cannot resolve the ethical question, we do offer effective suggestions on research-level pre-emptive mitigation routes applicable to all institutions regardless of geographic, economic, or social constraints.

The Procurement Conundrum

We used a bottom-up approach to estimate the scope 3 footprint associated with material procurement ("cradle-to-gate") for our research. A significant effort has been invested by the medical

and adjacent community to account for material procurement costs at both an individual and institutional level (Clabeaux *et al.*, 2020; Montoro *et al.*, 2023; Quann *et al.*, 2023; Maida *et al.*, 2024). Like other carbon accounts (McGain *et al.*, 2020; Maida *et al.*, 2024; Souter *et al.*, 2024), we used government-reported statistics on fuel conversion alongside reasonable approximations of the mode and route of transport. In the case of vial and fly provision, we acquired information about product assembly, location of distribution centres, weight of shipped products and amount of recyclable materials both via public means and by interacting with procurer sustainability representatives. However, necessary data concerning product manufacture, assembly, and distribution were often held back due to proprietary concerns. Specifically, we were unable to ascertain: i) the exact mode of transport used in sub-parts of the distribution chain, ii) the complete distribution route, iii) the location, number, or energy-demands of prior routes in the distribution chain (i.e., raw resource procurement), iv) the energy mix of the manufacturer factories, or v) manufacturer-level mitigation strategies. While we can make robust travel cost estimations if we know the start point of the distribution chain, the precision of the account is significantly impaired by a lack of industry information and transparency (Stenzel and Waichman, 2023). In some instances (e.g., gas canisters, chemical reagents, cotton flugs to seal *Drosophila* inside vials), we were unable to acquire any information related to procurement due to a lack of response to information requests. Nevertheless, the majority of distributors we contacted (3 of 5) were approachable, enthusiastic, receptive, and open to information requests, demonstrating how overcoming the initial energy barrier of reaching out to procurers can reveal novel and utile information. For instance, alongside learning about the procurement routes from the Bloomington *Drosophila* stock centre, we also learned the total volume of *Drosophila* distribution to laboratories worldwide in 2023. The future must see both procurement institutions and researchers attempt to track, estimate, and record carbon-related procurement information so we can better focus and evaluate emission mitigation targets. Researchers are capable of only so much when provided with incomplete information. Institutions must report on upstream procurement (e.g., routes, methods, and loads from primary producers) as well as downstream procurement information (e.g., routes, methods, and loads to consumers). The manufacturers and distributors that are first-movers in publicly accessible and accurate emission-related data will not just gain a significant foot in the carbon net-neutral landscape but will enable researchers to act as changemakers by making active choices to support more sustainable distributors and manufacturers, creating a race-to-openness by suppliers and distributors in and beyond academia.

Procurers and intermediate agents in the scientific resource supply chain often have highly useful information that can be easily accessed by direct contact. The highly connected, dynamic and demanding landscape for procurement often results in agents involved in the supply chain having

access to precise, accurate, and highly useful information. However, the sheer volume of data or the lack of obvious public uses for supply chain meta-data (e.g., number of orders, user's location, frequency of orders) often mean that it is not made publicly accessible, increasing the energy barrier for widespread, individual-led carbon accounting. For instance, direct contact with Bloomington *Drosophila* Stock Centre yielded disclosure of 2023 outflow information for domestic and worldwide *Drosophila* laboratories (e.g., 171,426 vials, 17 vials per order, single orders ranging from 1-200 vials, 50% of US to 50% international orders). This exemplifies how individual-led action can yield meta-data from procurers that can help to refine and scale up estimates of carbon footprints from the researcher to the community and international level.

Moving forward, we hope that community-driven action in neuroscience and adjacent disciplines will foster a culture of openness amongst our industry partners, kick-starting a race-to-openness on emissions data. The initiative shown by Scientific Laboratory Supplies and other companies demonstrates how researchers and suppliers can work together to inform more sustainable research practices. Indeed, the European Union (EU) have already begun legislating for carbon accounting at a higher industry level which will continue to see EU producers and distributors release energy and CO_2e-related information in the coming years (Dinh, Husmann and Melloni, 2023; Hummel and Jobst, 2024). Supporting these efforts is a rise in initiatives derisking and aiding stakeholders (e.g., multi-stakeholder initiatives) to effectively meet legislative targets (Romito, Vurro and Pogutz, 2024). At the individual level, researchers are beginning to calculate the carbon footprint of their research, generating robust datasets that enable effective policy implementation and accountability at the institutional level. Supporting the next generation of carbon literate researchers will multiply the impact of academic institutions as change-makers in the race towards net-neutral, informing procurement decisions that provide a market incentive for data openness among equipment producers and distributors.

The Future of Research CO_2e

To reach our climate targets, large-scale grid decarbonisation efforts must be complemented by technological and social innovation to improve the efficiency and accessibility of renewable resources, and increasing carbon literacy, with its attendant changes in individual behaviour (Sithole *et al.*, 2016). These actions may be hampered by institutional and individual complacency, redirection of decarbonisation funding to inefficient streams, and the rising dominance of high-energy industries (e.g., complexification of AI, blockchain mining for cryptocurrency) (Truby *et al.*, 2022; Cowls *et al.*, 2023). Even without such barriers, careful planning is necessary to avoid increases to scope 3 emissions when expanding renewable energy infrastructure (e.g., mineral mining for batteries,

artificial intelligent-required computer chips, renewable machinery, system-wide heat-pump adoption) with consideration for equipment longevity and recycling (Jackson, Meinke and Chandramohan, 2024).

Within academia, climate targets will undoubtedly be challenged by increasingly energy-intensive research methods and social resistance to short-term transition costs. Fortunately, high emission sectors including medicine (McGain and Naylor, 2014) and agriculture (Jebari *et al.*, 2024) are leading the way in carbon accounting for informed emissions mitigation, paving the way for other disciplines to interrogate their emissions landscapes, to develop strategies to meet institutional, national, and international emissions reduction targets (Zhao *et al.*, 2024). We believe that this effort will be most effective if individuals and institutions work together to collect accurate emissions data for efficient, equitable, and community-driven transitions to sustainable research practice.

Our work shows how individual researchers in any discipline can accurately and efficiently account for greenhouse equivalent emissions. Mirroring medical and clinical researchers, we have commenced an open-source carbon data store for *Drosophila* neuroscience research. Alongside our meta-analysis reported here, we point researchers to efforts at emissions tracking at all levels of research (Loyarte-López, Barral and Morla, 2020; Mariette *et al.*, 2022) that are aiding our understanding of how different research techniques, geographies, travel demands, and scientific practices affect carbon emissions. We encourage researchers at all levels to participate in building a codex of carbon accounts that will empower the scientific community to lead the way as a positive social force for climate accountability.

Methods

Power Estimation

The power usage of experimental and laboratory equipment was determined using RS Pro Energy Metres (Stock No: 178-5370; Model No. PM01; Stock No. 123-3230). The power demands of equipment associated with experiments (e.g., calcium imaging) was recorded for 1-3 instances of mock experiments by using the power metres interlocked from wall mains supply. The power of persistent equipment (e.g., incubators, fridges) was recorded over a 24-72 hr period in February-March 2023. We estimated the power usage of our analysis using the hardware analysis and monitoring software HiWinFO during analysis of experimental-related data (e.g., traces, Python-based visualisation) (https://www.techspot.com/downloads/5245-hwinfo64.html). Clamp metres (Stock No. 123-3230) were used to measure energy from air conditioning units. The high-powered equipment

for food generation and autoclaves precluded direct measurement for safety reasons, thus we resorted to maximum power calculations based on the equipment's industry reported metrics. The power usage of our laboratory spaces was monitored through direct building power metres reported by SystemsLink™ and subsequently applied to our research based on floor area (electricity: 71.48kWh/m^2; gas: 170.14kWh/m^2).

Direct CO_2 Release from Virgin Collection

The collection of *Drosophila* virgins for genetic crosses necessitates anaesthesia by direct application of CO_2 to sort flies by sex and fertility status. *Drosophila* adults are initially anaesthetised within their vial using a gas gun, then tipped onto a CO_2 pad where CO_2 is intermittently released to arrest movement. We estimated the direct release of CO_2 during virgin collection from a gas gun (SLS FlyStuff Blowgun FLY1042) through a graduated 100ml glass gas syringe (9L per minute) and from a CO_2 pad (SLS FlyStuff Flypad Standard FLY1208) using a fluid displacement method. We timed the application of CO_2 during virgin collecting amongst three researchers to arrive at the average CO_2 released per vial during virgin collection. We scaled up the measurement for heavy genetic screening laboratories based on reported vial load for two and three stage genetic constructs.

Power-to-eCO_2 Conversion

We utilised the open-source, freely available National Grid ESO's carbon intensity regional Carbon Intensity API to convert the power usage of equipment associated with experiments and persistent equipment to a valid equivalent carbon dioxide (CO_2e) estimation. For the 2023-4 period, count per month of experiments were recorded and translated into CO_2e estimations using the API. Specifically, we took the mean of the first two weeks of each month (June 2023-4) to calculate our monthly-associated research eCO_2 emissions. The detailed methodology of the regional carbon intensity API is available on GitHub (https://carbon-intensity.github.io/api-definitions/#carbon-intensity-api-v2-0-0).. Code for data extraction from the API, processing, and visualisation is available in our repository.

Travel Cost & Procurement Estimation

Estimates of CO_2e travel costs were made using a combination of the UK 2024 government's reported conversion factors (https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2024), self-reporting by ScotRail (https://www.scotrail.co.uk/carbon-calculator) and the ICAO Carbon Emissions Calculator (ICAO) (https://www.icao.int/environmental-protection/Carbonoffset/Pages/default.aspx). The methodology for each report is detailed through provided links. We used Google's Distance Matrix API to calculate the distance of journeys.

We estimated the CO_2e emissions associated with equipment transport during procurement based on the reported site of manufacture. Non-recyclable vials (FLY1312, Scientific Laboratory Supplies) are manufactured and assembled in Tijuana, Mexico. We aimed to estimate the range of associated CO_2e emissions for procurement from Tijuana to St Andrews based on distance matrix API calculations and reported destinations for travel. We assumed vial exports delivered by air freight came directly from Tijuana International Airport to Edinburgh Airport. We assumed cargo-based exports came from the main Mexican export port, Manzanillo Port. We assumed direct travel between the reported final destination of manufacture and the final procurement destination. *Drosophila* fly stocks were procured from Bloomington Indiana. We assumed air freight from Indianapolis International Airport to Edinburgh International Airport. We assumed that vehicle transport of both vials and flies used an average HGV per the UK government's reported emissions values.

Supporting Information

Table 1: Energy Costs and Model Types for Persistent and Experimental Equipment.

Lab Sphere	Type	Equipment	kWh	Model
Persistent		Incubator 19°C	0.070	Panasonic MIR-554-PE
		Incubator 25°C	0.010	
		Incubator 25L (19°C)	0.010	Vevor Reptile Incubator
		Incubator 25L (25°C)	0.070	
		Fridge 10°C	0.100	LEC (model no: L550WS, serial no: 7D 0144847)
		Fridge/Freezer (10°C/-13°C)	0.040	Liebherr Comfort
		Vial Freezer -20°C	0.400	Bush 43282301
		CO_2 Monitoring System	0.010	Flamefast CellarGuard
		Gas Heating System	8796	
		Electricity System	2138	
		Large AC System	0.644	Mitsubishi Electric AC/HP (MUZ-SF3SVE, 6 03468T)

		Small AC System	0.552	Daikin AC/HP (RXS50L2V1B) System
Virgin Collection/Preparation		LED	0.004	Euronex LE. 5208 AC100V-240V 90-7843
Saline Preparation		Water Purification	0.145	Millipore Q Water System F3J15741N + Suez Purite Deionizer
Experiments	Calcium Imaging	Camera & Manipulator	0.045	Andor XIon3 Camera (100ms) and MPC-200, TH4-200 Olympus & ROE-200_1849 Shutter
		Power Supply	0.014	CAIRN OptoLED Power Supply 3666
		Perfusion System	0.002	Kamoer KCP3-BIOW
		Computer & Interface	0.082	i7-8700 3.2GHz CPU, 16GB RAM, NVIDIA GeForce GTX 1080) & Interface (NI-USB-6229 National Instruments Digital I/O System, AD PowerLab Instrument 16/35 - PL3616-0154
	Electrophysiology & Optogenetics	Camera & Manipulator	0.045	Andor XIon3 Camera and MPC-200, TH4-200 Olympus Microscope Accessory + ROE-200_1849 Shutter Instrument Manipulator
		Power Supply	0.014	CAIRN OptoLED Power Supply 3666
		Computer & Interface	0.360	i7-8700 3.2GHz CPU, 16GB RAM, NVIDIA GeForce GTX 1080 & NI-USB-6229 National Instruments Digital I/O System, AD PowerLab Instrument 16/35 - PL3616-0154
		Amplifier	0.007	AM System Differential AC Amplifier Model (#59721, 1700)
	Dual Colour Imaging	Camera	0.027	ORCA-Fusion C14440 Hamamatsue
		Spinning Disc	0.006	Emission White Filter Spinning Disc CREST
		Light Source	0.150	Lumencore
		Computer & Interface	0.234	HP Z9, 2x Intel Xeon ® Silver 4215 CPU @ 2.5GHz, 2494MHz, 8 cores(s), 16 logical processors, 192GB RAM) + Intel Screen
	Behavioural Tracking	Computer & Camera	0.054	HP i7-8700 3.2GHz, 3192 MHz, 6 core(s), 12 logical processes, 16GB RAM & Navitar Zoom 7000
		Light Stimulation	0.006	Thorlabs DC2200 + SOLIS-3L-light 600mA constant stimulation for 10s-20s-30
		IR Light	0.006	Andoer IR49S Mini IR
Analysis		Computer & Interface	0.121	12th Intel i9-12900 HK, 14 cores, 20 logical processors, 64GB RAM, NVIDIA GeForce RTX 3070 Ti GPU + Acer Monitor
Food Generation		Cooking & Mixer	7.536 (max)	Cleveland 13L
Vial Disposal		Autoclave	10 (max)	Astell Scientific, SPBN21642, ASB270BT65.

Table 2: CO_2e Research Costs for One Researcher 2023-4.

The yearly CO_2e (kg) is calculated on the rolling average of the South Scotland kWh/CO_2e conversion with per task CO_2e the average of the year.

Task	Per Task CO_2e (g/hr)	Yearly Ns	Time Per Task (hr)	Yearly CO_2e (g)
Virgin Collection	1.60	972	~	1555.20
Preparation	0.18	132	~	23.76
Behavioural Tracking	0.40	8	2.5	3.53
Calcium Imaging	0.80	94	1.0	69.34
Dual Colour Imaging	2.20	33	0.3	24.00
Optogenetics & Electrophysiology	8.70	16	2.5	539.23
Lab Task	**CO_2e (g/vial)**	**Yearly Ns**	**Time per Task (hr) (max vials)**	**Yearly CO_2e (g)**
Food Generation	0.21	8400	1 (400)	3200.60
Vial Disposal	1.47		2 (150)	2240.00

Table 3: Travel-related CO_2e Costs for PhD-related Travel for Training and Conferences.

Route	Method	Instances (2023-4)	Yearly CO_2e (kg) without RF	Yearly CO_2e (kg) with Median RF
Leuchars – Edinburgh	Train	2	11.60	11.60
Leuchars – Stirling		1	9.68	9.68
Leuchars – Aberdeen		1	8.54	8.54
St Andrews – Leuchars	Bus	4	7.57	7.57
St Andrews – Dundee		1	4.15	4.15
Edinburgh – Frankfurt – Vienna	Plane	1	380.00	1330.00

Table 4: Procurement-related CO_2e costs for Vial and Fly Stocks in 2023-4 Research Year

Equipment	Count	Weight per Item (kg)	Total Estimated Travel Distance (HGV + Flight) (km)	CO_2e (kg) (HGV - Flight)	Total Estimated Travel Distance (HGV + Cargo) (km)	CO_2e (kg) (HGV – Shipping)
Vials (500)	17	0.16	8464	9.23	12181	0.07
Optic Filters (4 filters, 1 mirror)	1	0.06	8287	9.11	12532	0.01
Fly Stocks (4)	12	0.08	6317	6.79		

Table 5: Yearly Procurement Quantity for One PhD Student

Equipment	Yearly Used Mass (g)	Quantity	Provider	Serial/Batch Code
NaCl	157.50	< 1	Sigma Aldrich™	S9888-1KG
		< 1	VMR™	21A144160
KCl	7.45	< 1	Sigma Aldrich™	P9333-500G
		< 1	VMR™	14I170013
$CaCl_2$ x $2H_20$	5.90	< 1	VMR™	14G090030
$MgCl_2$ x $6H_2O$	16.25	< 1	Sigma Aldrich™	M2670-500G
		< 1	VMR™	14H18004
TES Buffer	22.95	< 1	Sigma Aldrich™	T1375-100G
		< 1	Thermo Fisher Scientific™	B21819.30
Sucrose	246.50	< 1	VMR™	201284121
Gas Canister	39000	6	BOC™	BOC UN1013 EC 204-696-9
Yeast Food	6240			
Flugs	624	< 1	Scientific Laboratory Supplies™	FLY1198

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Conflicts of Interest

No declared conflict of interest.

Data Availability

The data is available upon reasonable request to the corresponding author.

Author's Contributions

S.R.P. and W.V.S. conceived the study. W.V.S. and A.B. determined scope 1 emissions. W.V.S. and R.S. performed energy usage estimates. W.V.S. and S.R.P. engaged with suppliers and distributors to estimate scope 3 emissions. W.V.S. constructed analytical pipelines and drafted the figures and manuscript. A.B. provided assistance with emissions calculations and revised the manuscript. W.V.S. and A.B. finalised the figures. S.R.P. supervised the project.

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