Green Algorithms: Quantifying the carbon emissions of computation

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Abstract

Climate change is profoundly affecting nearly all aspects of life on earth, including human societies, economies and health. Various human activities are responsible for significant greenhouse gas emissions, including data centres and other sources of large-scale computation. Although many important scientific milestones have been achieved thanks to the development of high-performance computing, the resultant carbon impact has been underappreciated. In this paper, we present a methodological framework to estimate the carbon impact (CO₂ equivalent) of any computational task in a standardised and reliable way, based on the running time, type of computing core, memory used and the efficiency and location of the computing facility. Metrics to interpret and contextualise carbon impact are defined, including the equivalent distance travelled by car or plane as well as the number of tree-months necessary for carbon sequestration. We develop a freely available online tool, Green Algorithms (www.green-algorithms.org), which enables a user to estimate and report the environmental impact of their computation. The Green Algorithms tool easily integrates with computational processes as it requires minimal information and does not interfere with existing code, while also accounting for a broad range of CPUs, GPUs, cloud computing, local servers and desktop computers. Finally, by applying Green Algorithms, we quantify the environmental impact of algorithms used for particle physics simulations, weather forecasts and natural language processing. Taken together, this study develops a simple generalisable framework and freely available tool to quantify the carbon impact of nearly any computation. Combined with a series of recommendations to minimise unnecessary CO₂ emissions, we hope to raise awareness and facilitate greener computation.
Introduction

The concentration of greenhouse gases in the atmosphere has a dramatic influence on climate change with both global and locally focused consequences, such as rising sea levels, devastating wildfires in Australia, extreme typhoons in the Pacific, severe droughts across Africa, as well as repercussions for human health.

With 100 megatonnes of CO$_2$ emissions per year, similar to American commercial aviation, the contribution of data centres and high-performance computing facilities to climate change is substantial. So far, rapidly increasing demand has been paralleled by increasingly energy-efficient facilities, with overall electricity consumption of data centres somewhat stable. However, this stability is likely to end in the coming years, with a best-case scenario forecasting a three-fold increase in the energy needs of the sector.$^{1,2}$

Advances in computation, including those in hardware, software and algorithms, have enabled scientific research to progress at unprecedented rates. Weather forecasts have increased in accuracy to the point where 5-day forecasts are approximately as accurate as 1-day forecasts 40 years ago,$^3$ physics algorithms have produced the first direct image of a black hole 55 million light-years away$^{4-6}$, the human genome has been mined to uncover thousands of genetic variants for disease$^7$, and machine learning permeates many aspects of society, including economic and social interactions$^8-11$. However, the costs associated with large-scale computation are not being fully captured.

Power consumption results in greenhouse gas (GHG) emissions and the environmental costs of performing computations using data centres, personal computers, and the immense diversity of architectures are unclear. While programmes in green computing (the study of environmentally responsible information and communications technologies) have been developed over the past decade, these mainly focus on energy-efficient hardware and cloud-related technologies$^{12-14}$.

With widely recognised power-hungry and expensive training algorithms, deep learning has begun to address its carbon footprint. Machine learning (ML) models have grown exponentially in size over the past few years$^{15}$, with some algorithms training for thousands of core-hours, and the associated energy consumption and cost have become a growing concern$^{16}$. In natural language processing (NLP), Strubell et al.$^{17}$ found that designing and training translation engines can emit between 0.6 and 280 tonnes of CO$_2$. While not all NLP algorithms require frequent retraining, algorithms in other fields are run daily or weekly, multiplying their energy consumption.

Previous studies have made advances in estimating carbon emissions of computation but have limitations which preclude broad applicability. These limitations include the requirement that users self-monitor their power consumption$^{17}$ and are restricted with respect to hardware (e.g. GPUs and/or cloud systems$^{18,19}$), software (e.g. Python package integration$^{19}$), or applications (e.g. machine learning)$^{17-19}$. To facilitate green computing and widespread user uptake, there is a clear, and arguably urgent, need for both a general and easy-to-use methodology for estimating carbon impact that can be applied to any computational task.

In this study, we present a simple and widely applicable method and a tool for estimating the environmental impact of computation. The method takes into account the different sources of carbon emissions, such as processors and memory, while balancing accuracy and practicality. The online calculator (www.green-algorithms.org) implements this methodology and provides further context by interpreting carbon impact using travel distances and carbon sequestration. We use the Green
Algorithms method to estimate the carbon footprint of particle physics simulations, weather forecast models, and NLP algorithms as well as the carbon effects of distributed computation using multiple CPUs. Finally, we make recommendations to increase green computation as well as discuss the limitations of our approach.

Methods

The environmental impact of an algorithm depends on two factors: the energy needed to run it and the carbon impact of producing such energy. The former depends on the computing resources used (e.g. number of cores, running time, data centre efficiency) while the carbon footprint of energy production, called carbon intensity, depends on the location and methods used (e.g. nuclear, gas or coal).

When estimating these parameters, accuracy and feasibility must be balanced. This study focuses on a methodology that can be easily and broadly adopted by the community. The framework presented requires no extra computation nor involves monitoring tools.

Energy consumption

We model an algorithm’s energy requires as a function of running time, the number, type and process time of computing cores (CPU or GPU), the amount of memory mobilised and the power draw of these resources. The model further includes the efficiency of the data centre, i.e. how much extra power is necessary to run the facility (e.g. cooling and lighting).

Similar to previous works, our estimate is based on the power draw from processors and memory, as well as the PUE. However, for the tool to adapt to different numbers of cores and different usage levels, it is important to include a unitary power draw (per core and per GB of memory) and the processor’s usage factor. We express the energy consumption \( E \) (in kilowatt-hours, kWh) as:

\[
E = t \times (n_c \times P_c \times u_c + n_m \times P_m) \times PUE \times 0.001
\]

where \( t \) is the running time (hours), \( n_c \) the number of cores and \( n_m \) the size of memory available (gigabytes). \( u_c \) is the core usage factor (between 0 and 1). \( P_c \) is the power draw of a computing core and \( P_m \) the power draw of the memory (Watt). \( PUE \) is the efficiency coefficient of the data centre.

The assumptions made regarding the power draw of the processor, memory and storage are discussed below. It has been previously shown that the power draw of the motherboard is negligible.

Power draw of the computing core

The metric commonly used to report the power draw of a processor, either CPU or GPU, is its thermal design power (TDP, in Watt) and is provided by the manufacturer. TDP values frequently correspond

\[\text{a} \quad \text{Power (in Watt, W) measures the instantaneous draw of a component. Energy (in kilowatt-hours, kWh) measures the power draw over time and is obtained by multiplying the power draw by the running time.}\]

\[\text{b} \quad \text{By data centre, we mean the facility hosting the cores and memory, which may not be a dedicated data centre.}\]
to CPU specifications which include multiple cores, thus here TDP values are normalised to per-core. While TDP is not a direct measure of power consumption, rather the amount of heat a cooling system dissipates during regular use - it is commonly considered a reasonable approximation.

The energy used by the processor is the power draw multiplied by processing time, controlled by the usage factor. However, processing time cannot be known \textit{a priori} and tracking can be impractical at scale, particularly when loads vary over time. In practice, modelling exact processing time necessitates the re-running of jobs, which is likely to generate unnecessary emissions. Therefore, the online tool gives the option to specify the core usage and when it is unknown, we make the simplifying assumption that core usage is 100% of run time ($u_c = 1$ in (1)).

**Power draw from memory**

Memory power draw is mainly due to background consumption with a negligible contribution from the workload and database size\textsuperscript{21}. Moreover, the power draw is mainly affected by the total memory allocated, not by the actual size of the database used, because the load is shared between all memory slots which keeps every slot in a power-hungry active state. Therefore, the primary factor influencing power draw from memory is the quantity of memory mobilised, which simply requires an estimation of the power draw per gigabyte. Measured experimentally, this has been estimated to be 0.3725 W/GB\textsuperscript{21,22}. For example, requesting 29GB of memory draws 10.8 W, which is the same as one core of a popular Core-i5 CPU. **Supplementary Figure 1** further compares the power draw of memory to a range of popular CPUs.

**Power draw from storage**

The power draw of storage equipment (HDD or SSD) varies significantly with workload\textsuperscript{23}. However, in regular use, storage is typically solicited far less than memory and is mainly used as a more permanent record of the data, independently of the task at hand. In idle mode (i.e. not servicing a request but ready to begin the next one), non-optimised HDDs rarely consume more than 6W for 1TB of storage and modern SSDs can draw as little as 0.6W for 800GB of storage\textsuperscript{23}. Under conservative assumptions, storage power draw would be 0.006 W/GB. As above, by comparison, the power draw of memory (0.3725 W/GB) and a Core-i5 CPU (10.8W/core) are more than an order of magnitude greater. While the researcher overhead for approximating storage usage may not be substantial, it is unlikely to make a significant difference to overall power usage (and carbon emissions) estimation. Therefore, we do not consider power consumption of storage in this work.

**Energy efficiency**

Data centre energy consumption includes additional factors, such as server cooling systems and lighting. The efficiency of a given data centre is measured by the Power Usage Effectiveness (PUE), defined as the ratio between the total power supplied to the facility and the power used by computing equipment:

$$PUE = \frac{P_{\text{total}}}{P_{\text{compute}}} \quad \text{(2)}$$

A data centre PUE of 1.0 represents an ideal situation where all power supplied to the building is utilised by computing equipment. The global average of data centres has been estimated as 1.67 in 2019\textsuperscript{24}. While data centres with relatively inefficient PUE may not report it as such, some data centres and companies have invested significant resources to bring their PUEs as close to 1.0 as possible;
for example, Google has utilised machine learning to reduce its global yearly average PUE to 1.10\textsuperscript{25,26}.

**Environmental impact of energy production**

To control for variation in environmental impacts from different electricity production methods, we utilise carbon dioxide equivalent (CO\textsubscript{2}e) to summarise the global warming effects of GHG. For a given GHG mix emitted when producing energy, this indicator represents the amount of CO\textsubscript{2} with the same environmental impact. The environmental impact of producing energy is measured by the Carbon Intensity (CI), i.e. the carbon footprint of producing 1 kWh of energy. This varies significantly between locations due to the broad range of production methods (Supplementary Figure 2), e.g. from 11 gCO\textsubscript{2}e/kWh in Norway (mainly powered by hydro) to 900 gCO\textsubscript{2}e/kWh in Australia (mainly powered by coal and gas)\textsuperscript{27,28}.

**Estimation of carbon impact**

The carbon impact \( C \) (in gCO\textsubscript{2}e) of producing a quantity of energy \( E \) (in kWh) from sources with a carbon intensity \( CI \) (in gCO\textsubscript{2}e/kWh) is then:

\[
C = E \times CI \tag{3}
\]

By putting together equations (1) and (3), we obtain the long form equation of the carbon impact \( C \):

\[
C = t \times (n_c \times P_c \times u_c + n_m \times P_m) \times \text{PUE} \times CI \times 0.001 \tag{4}
\]

**CO\textsubscript{2}e of driving and air travel**

We contextualise gCO\textsubscript{2}e by estimating an equivalence in terms of distance travelled by car or by passenger aircraft. Previous studies have estimated the emissions of the average passenger car in Europe as 175 gCO\textsubscript{2}e/km\textsuperscript{29,30} (251 gCO\textsubscript{2}e/km in the United States\textsuperscript{31}). The emissions of flying on a jet aircraft in economy class has been estimated between 138 and 255 gCO\textsubscript{2}e/km/person, depending on the length of the flight\textsuperscript{30}. We use three reference flights: Paris to London (50,000 gCO\textsubscript{2}e), New York to San Francisco (570,000 gCO\textsubscript{2}e) and New York to Melbourne (2,310,000 gCO\textsubscript{2}e)\textsuperscript{32}.

**CO\textsubscript{2} sequestration by trees**

Trees play a major role in carbon sequestration. To provide a metric of reversion for CO\textsubscript{2}e, we compute the number of trees needed to sequester the emissions of a given computation. We define the metric tree-months, the number of months a mature tree needs to absorb a given quantity of CO\textsubscript{2} emissions. While the amount of CO\textsubscript{2} sequestered by a tree per unit time depends on a number of factors, it has been estimated that a mature tree sequesters approximately 11.4 kg CO\textsubscript{2} per year\textsuperscript{33}, giving the multiplier in tree-months a value of approximately 1kg of CO\textsubscript{2} per month.

**Pragmatic scaling factor**

Many analyses are presented as a single run of a particular algorithm or software tool; however, this is rarely the true number of times computations were performed. Algorithms are run multiple times, sometimes hundreds, systematically or manually, with different parameterisations. Statistical models may include any number of combinations of covariates, fitting procedures, etc. Since it generally has

\textsuperscript{c} Sometimes also called CO\textsubscript{2}eq, CO\textsubscript{2} equivalent or CDE.
a multiplying effect, it is important that multiple runs of approximately the same computation are included in the carbon impact. We attempt to empirically estimate the number of times a computational is performed in practice by defining the pragmatic scaling factor (PSF), a scaling factor by which the estimated carbon impact is multiplied.

The value and causes of the PSF vary greatly between tasks. In machine learning, tuning the hyper-parameters of a model requires hundreds, if not thousands, of runs, while other tools require less tuning and can sometimes be run a smaller number of times. As per published or the user’s own experience, the PSF should be estimated for any specific task; however, in Green Algorithms we provide for, and recommend that, each user estimate their own PSF.

Figure 1: The Green Algorithms calculator (www.green-algorithm.org)
Results

We developed a simple method which estimates the carbon impact of an algorithm based on a number of factors, including the hardware requirements of the tool, the runtime and the location of the data centre (Methods). Using PSF, we further augment our estimates by allowing for empirical estimates of repeated computations for a particular task, e.g. parameter tuning and trial-and-errors. The resultant gCO₂e is compared to the amount of carbon sequestered by trees and the emissions of common activities such as driving a European passenger car and air travel. We designed a freely available online tool, Green Algorithms (www.green-algorithm.org; Figure 1), which implements our approach and allows users to reconfigure their computations or estimate the carbon savings or costs of redeploying them on other architectures.

We apply this tool to a range of algorithms selected from a variety of scientific fields: physics (particle simulations and DNA irradiation), atmospheric sciences (weather forecasting), and machine learning (natural language processing) (Figure 2). For each task, we curate published benchmarks and use www.green-algorithms.org to estimate the carbon emissions (Methods). For parameters independent of the algorithm itself, we use average worldwide values, such as the worldwide average PUE of 1.67 and carbon intensity of 475 gCO₂e/kWh.

Figure 2: Carbon emissions (gCO₂e) for a selection of algorithms, with and without their Pragmatic Scaling Factor.

Particle physics simulations

In particle physics, complex simulations are used to model the passage of particles through matter. Geant4 is a popular toolkit based on Monte-Carlo methods with wide-ranging applications, such as the simulation of detectors in the Large Hadron Collider and analysis of radiation burden on patients in clinical practice or external beam therapy. Meylan et al. investigated the biological effects of ionising radiations on DNA on an entire human genome (6.4 × 10⁹ nucleotide pairs) using GEANT4-DNA, an extension of GEANT4.
To quantify the DNA damage of radiation, they run experiments with photons of different energy, from 0.5 MeV to 20 MeV. Each experiment runs for three weeks to simulate 5,000 particles (protons) using 24 processing threads and up to 10GB of memory. Using the Green Algorithms tool, and assuming an average CPU power draw (such as the Xeon E5-2680, capable of running 24 threads on 12 cores), and worldwide average values for PUE and carbon intensity, we estimated that a single experiment emits 49,465 gCO₂e. When taking into account a PSF of 11, corresponding to the 11 different energy levels tested, the carbon impact of such study is 544,115 gCO₂e. Using estimates of car and air travel (Methods), 544,115 gCO₂e is approximately equivalent to driving 3,109 km or flying economy from New York to San Francisco. In terms of carbon sequestration (Methods), it would take a mature tree 48 years to remove the carbon emissions of this study run from the atmosphere (573 tree-months).

GEANT4 is a versatile toolbox; it contains an electromagnetic package simulating particle transport in matter and high energy physics detector response. Schweitzer et al. use a standardised example, TestEm12, to compare the performances of different hardware configurations.

A common way to reduce the running time of algorithms is to distribute the computations over multiple processing cores. If the benefit in terms of time is well documented for each task, as in Schweitzer et al., the environmental impact is usually not taken into account. Schweitzer et al. studied the impact of running TestEm12 on a variable number of cores, from 1 to 60 (i.e. a full Xeon Phi CPU). With the Green Algorithms tool, we estimated the carbon impact of each configuration (Figure 3), which shows that increasing the number of cores up to 15 improves both running time and carbon emissions. However, when multiplying the number of cores further by 4 (from 15 to 60), the running time is only halved, resulting in a two-fold increase in emissions, from 237 to 481 gCO₂e. Generally, if the reduction in running time is lower than the relative increase in the number of cores, distributing the computations will worsen the carbon impact. For any parallelised computation, there is likely to be an optimal number of cores for minimal carbon emissions.

![Figure 3: Effect of parallelisation using multiple cores on run time and carbon emissions using TestEm12 GEANT4 simulation.](image-url)
Weather forecasting

Weather forecasts are based on sophisticated models simulating the dynamics between different components of the earth (such as the atmosphere and oceans). Operational models face stringent time requirements to provide live predictions to the public, with a goal of running about 200-300 forecast days (FDs) in one (wall clock) day. Neumann et al. present the performances of two models in use for current weather forecasts: (i) the Integrated Forecast System (IFS) used by the European Centre for Medium-Range Weather Forecasts (ECMWF) for 10-day forecasts, and (ii) the ICOSahedral Non-hydrostatic (ICON) designed by the German Weather Service (Deutscher Wetterdienst, DWD) and whose predictions are used by more than 30 national weather services.

The configurations in daily use by the ECMWF include a supercomputer based in Reading, UK, which has a PUE of 1.45, while ICON is run on the German Meteorological Computation Centre (DMRZ) based in Germany (PUE unknown). Neumann et al. ran their experiments on hardware similar to that equipped by both facilities, “Broadwell” CPU nodes (Intel E5-2695v4, 36 cores) and minimum 64GB memory per node. We utilise these parameters for our CO₂e emission estimates. It is important to note that ICON and IFS solve slightly different problems, and therefore are not directly comparable.

The DWD uses ICON with a horizontal resolution of 13 km and generates a forecast day in 8 minutes. Based on the experiments run by Neumann et al., this requires 575 Broadwell nodes (20,700 CPU cores). We estimate that generating one forecast day emits 15,915 gCO₂e (17 tree-months). With a running time of 8min/FD, ICON can generate 180 forecast days in 24 hours. When taking into account this pragmatic scaling factor of 180, we estimated that each day the ICON weather forecasting algorithm releases approximately 2,864,704 gCO₂e, equivalent to driving 16,370 km or flying from New York to San Francisco five times. In terms of carbon sequestration, the emissions of each day of ICON weather forecast was equivalent to 3,015 tree-months.

At ECMWF, IFS makes 10-day operational weather forecasts with a resolution of 9 km. To achieve a similar threshold of 180 FDs/day, 128 Broadwell nodes are necessary (4,608 cores). Using the PUE of the UK ECMWF facility (1.45), we estimate the impact of producing one forecast day with IFS to be 1,819 gCO₂e. Using a PSF of 180 for one day’s forecast, we estimated emissions of 327,379 gCO₂e, equivalent to driving 1,871 km or three return flights between Paris and London. These emissions are equivalent to 345 tree-months.

Furthermore, we modelled the planned scenario of the ECMWF transferring its supercomputing to Bologna, Italy, in 2021. Compared to the data centre in Reading, the new data centre in Bologna is estimated to have a more efficient PUE of 1.27. Prima facie this move appears to save substantial carbon emissions; however, it is notable that the carbon intensity of Italy is 18% higher than the UK. Unless the sources of electricity for the data centre in Bologna are different from the rest of Italy and in the absence of further optimisations, we estimated that the move would result in a 3.3% increase in carbon emissions from the ECMWF (from 327,379 to 338,130 gCO₂e).

National language processing

In natural language processing (NLP), the complexity and financial costs of model training are major issues. This has motivated the development of language representations that can be trained once.

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The horizontal resolution represents the level of geographical detail achieved when modelling the different weather phenomenon.
to model the complexity of natural language, and which could be used as input for more specialised algorithms. The BERT (Bidirectional Encoder Representations from Transformers)\textsuperscript{32} algorithm is a field leader which yields both high performance and flexibility: state-of-the-art algorithms for more specific tasks are obtained by fine-tuning a pre-trained BERT model, for example in scientific text analysis\textsuperscript{53} or biomedical text mining\textsuperscript{54}. Yet, while the BERT model is intended to avoid retraining, many data scientists, perhaps understandably, continue to recreate or attempt to improve upon BERT, leading to redundant and ultimately inefficient computation as well as excess CO$_2$e emissions. Even with optimised hardware (such as NVIDIA Volta GPUs), a BERT training run may take three days or more\textsuperscript{55}.

Using these optimised parameters, Strubell et al.\textsuperscript{17} showed that a run time of 79 hours on 64 Tesla V100 GPUs was necessary to train BERT, with a usage factor of the GPUs of 62.7%. With the Greens Algorithms calculator, we estimated that a BERT training run would emit 754,407 gCO$_2$e (driving 4,311 km in a European car; 1.3 flights from New York to San Francisco; and 794,113 tree-months). When considering a conservative PSF of 100 for hyperparameters search, we obtain a carbon impact of 75,440,740 gCO$_2$e.

While BERT is a particularly widely utilised NLP tool, Google has also developed a chatbot algorithm, Meena, which was trained for 30 days on a TPU-v3 Pod containing 2,048 Tensor Processing Unit (TPU) cores\textsuperscript{56}. There is limited information on the power draw of TPU cores and memory; however, the power supply of this pod has been estimated to be 288 kW\textsuperscript{57}. Using a run time of 30 days, assuming full usage of the TPUs and ignoring memory power draw, the Greens Algorithms calculator estimated that Meena training emitted 164,488,329 gCO$_2$e, which corresponds to 173,145 tree-months or 71.2 flights between New-York and Melbourne.

Discussion

The method and Green Algorithms tool presented here provides users with a practical way to estimate the carbon impact of their computations. The online calculator is simple to use and generalizable to nearly any computational task. We applied the Green Algorithms calculator to a variety of tasks, including particle physics simulations, weather forecasting and natural language processing, to estimate their relative and ongoing carbon impact. Real world changes to computational infrastructure, such as moving data centres, was also quantifiable in terms of carbon emissions and was shown to be of substantive importance, e.g. moving data centres may attain a more efficient PUE but a difference in carbon intensity may negate any efficiency gains, potentially making such a move more detrimental to the environment.

Our work substantially enhances and extends prior frameworks for estimating the environmental impacts of computation. In particular, we have integrated previously unclear factors such as running time, processor types, memory and geographic location in the context of algorithms. Besides drawing attention to the growing issue of carbon emissions of data centres, one of the benefits of presenting a detailed open methodology and tool is to provide users with the information they need to reduce their environmental footprint. This reduces the burden on the user, so they are not required to either measure the power draw of hardware manually nor use a limited range of cloud providers for their computations. As presented in the Methods, the carbon impact of an algorithm can be broken down to a small number of key, easily quantifiable elements, such as number of cores, memory size and
usage factor, making the method highly flexible. Perhaps the most important challenge in green computing is to make the estimation and reporting of carbon impact a standard practice. This requires transparent and easy-to-use methodology, such as the Green Algorithms calculator (www.green-algorithms.org) and open-source code and data presented here (see Code availability).

Our approach has a number of limitations. First, we do not consider the case of hyperthreading; thus, by using TDP we may be substantially underestimating power draw. It has been shown that modern processors can consume up to twice the indicated TDP, mainly due to hyperthreading. The TDP value remains a sensible estimate of the base consumption of the processor, but users using hyperthreading should be aware of the impact on power consumption. Second, while the power consumption from storage is usually minimal, if central storage is constantly queried by the algorithm (e.g. to avoid overloading memory), this can be an important factor in power draw; however, there are resources which can be utilised if the algorithm is designed to be heavily storage reliant. Third, while some averaging is necessary, the energy mix of a country varies by the hour. For example, South Australia relies on wind and gas to produce electricity, however, its carbon intensity can vary between 112 to 592 gCO₂e/kWh within one day, depending on the quantity of coal-produced electricity imported from the neighbouring state of Victoria. Although most countries are relatively stable, these outliers may require a finer estimation. Our online calculator uses averaged values sourced from government reports. Fourth, there is no official certification or standardised approach to calculating the PUE of a data centre, making it prone to bias. Reporting of PUE is highly variable from yearly averages to the best-case scenario, e.g. in winter when minimal cooling is required (as demonstrated by Google’s quarterly results). Although some companies present well-justified results, many PUEs have no or insufficient justification. Moreover, the power draw of large facilities is averaged over a pool of users who have highly variable usages, from website hosting to HPC, meaning that the PUE reported is not necessarily the efficiency factor of the task at hand. PUE is inaccurate when computations are run on a laptop or desktop computer. As the device is used for multiple tasks simultaneously, it is impossible to estimate the power overhead due to the algorithm. In the calculator, we use a PUE of 1 because of the lack of information, but we caution this should not be interpreted as a sign of efficiency. Even though discrepancies will remain, an accurate, transparent and certified estimation of PUE would be a substantial step for the computing community. Fifth, the carbon impacts in the Results are based on manual curation of the literature. When parameters such as usage factor or PUE were not specified, we made some assumptions (100% core usage, or using average PUE) that can explain discrepancies between our estimates and the real emissions. For best results, authors should estimate and publish their emissions.

These are various, realistic actions one can take to reduce the carbon footprint of their computation. Acting on the various parameters in Green Algorithms (see Methods), is a clear and easy way approach. Below, we describe a selection of practical changes one can make:

Algorithm optimisation: Increasing the efficiency of an algorithm can have myriad benefits, even apart from reducing carbon footprint. Therefore, we highly recommend this and foresee algorithm optimisation as one of the most productive, easily recognisable core activities of green computing. While speed is an obvious efficiency gain, part of algorithm optimisation also includes memory minimisation. The power draw from memory mainly depends on the memory requested, not the actual memory used, and the memory requested is often the peak memory needed for one step of the algorithm (typically a merge or aggregation). By optimising these steps, one can easily reduce energy consumption.
Reduce the Pragmatic Scaling Factor: Limiting the number of times an algorithm, especially those that are power hungry, is run is perhaps the easiest way to reduce carbon footprint. Relatedly, best practices to limit PSF (as well as financial cost) include limiting parameter fine-tuning to the minimum necessary and defining a minimal scale for debugging.

Choice of data centre: Carbon footprint is directly proportional to data centre efficiency and the carbon intensity of the location. Data centre efficiency (PUE) varies widely between facilities but, in general, large data centres optimise cooling and power supply, reducing the energy overhead and make them more efficient than personal servers. Notably, a 2016 report estimated that if 80% of small US data centres were aggregated into hyperscale facilities, energy usage would reduce by 25%\textsuperscript{60}. For users to make informed choices, data centres should report their PUE and other energy metrics. While large providers like Google or Microsoft widely advertise their servers’ efficiency\textsuperscript{25,61}, smaller structures often do not. Relatedly, carbon intensity is perhaps the parameter which most affects total carbon footprint because of inter-country variation. It may be possible to choose a location with up to 60-fold greener energy mix.

Offsetting carbon emissions: Carbon offsetting is a highly flexible way to compensate for carbon emissions. An institution or a user themself can directly support reductions in CO$_2$ or other greenhouse gases, e.g. fuel-efficient stoves in developing countries, reducing deforestation or hydroelectric or wind-based power plants\textsuperscript{62,63}. As there are intricate international legislations and competing standards, we present here an overview and point at some resources. Multiple international standards regulate the purchase of carbon credits and ensure the efficiency of the projects supported\textsuperscript{64}. Most of the well-established standards are managed by non-profits and abide by the mechanisms set in place by the Kyoto protocol (in particular Certified Emission Reduction)\textsuperscript{65} and the PAS 2060 Carbon Neutrality standard from the British Standards Institution\textsuperscript{66}. Although the primary aim is carbon offsetting, projects are often also selected in line with the United Nations’ Agenda 30 for Sustainable Development\textsuperscript{67}, a broader action plan addressing inequalities, food security and peace. Amongst the most popular standards are the Gold Standard (founded by WWF and other NGOs)\textsuperscript{68}, Verra (formerly Verified Carbon Standard)\textsuperscript{69} and the American Carbon Registry (a private voluntary greenhouse gas registry)\textsuperscript{70}. In addition to direct engagement with these standards, platforms like Carbon Footprint\textsuperscript{62} select certified projects and facilitate the purchase of credits.

Conclusions

The framework presented here is generalizable to nearly any computation and may be used as a foundation for other aspects of green computing. The carbon emissions of computation are substantial and may be affecting the climate. We therefore hope that this new tool and metrics raise awareness of these issues as well as facilitate pragmatic solutions which may help to mitigate the environmental consequences of modern computation. Overall, with the right tools and practices, we believe HPC and cloud computing can be immensely positive forces for both improving the human condition and saving the environment.
Data availability

All data used for the calculator is available on GitHub:
https://github.com/GreenAlgorithms/green-algorithms-tool/tree/master/data.

Code availability

All code supporting the calculator is available on GitHub:
https://github.com/GreenAlgorithms/green-algorithms-tool

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Supplementary Materials

Supplementary Figure 1: Comparison of power draw (per core) between popular CPUs and memory.
Supplementary Figure 2: Worldwide carbon intensity distribution by countries, curated from 28.