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CF Carbon Footprints

Land Use Systems

Low Carbon Footprint

- Reduced tillage
- Minimal chemical use
- Tree incorporation
- Multispecies systems

↓

- Sustained yields, multiple products
- Higher economic returns in the long term
- Improved soil health
- Better ecosystem services

High Carbon Footprint

- Heavy mechanization
- High agrochemical use
- Single species systems
- Ecological destruction

↓

- Soil and land deterioration
- Diminished biodiversity
- Inefficient resource utilization
- Devastation caused by climate change

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The first issue of Carbon Footprints.

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Carbon Footprints

Editorial

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Carbon footprints and land-use systems

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Abstract

Carbon Footprint (CFP) refers to the emission of all greenhouse gases (GHGs) during a given period by any activity or entity. The standard unit for measuring it is the carbon dioxide equivalent (CO_{2eq}), such that the impact of each GHG is expressed in terms of the amount of CO_2 that would create the same amount of warming. It is widely recognized that the 2020 global value for average per capita CFP (estimated as 4.47 Mg CO_{2eq}) is not sustainable and that it must be reduced to < 2 Mg CO_{2eq} if global warming is to be limited to 2°C. Recent estimates show that 31% of human-caused GHG emissions originate from the world's agri-food systems, the major sources being deforestation, livestock production (from enteric fermentation and manure), food waste disposal, and fossil fuel use (by farms and the food-retail sector). Land application of chemicals such as fertilizers, weedicides, and insecticides is the most significant factor in the AFOLU (agriculture, forestry, and other land-use) sector. Enhancement of the natural process of terrestrial C sequestration in soil and vegetation is a widely recognized approach to reducing the AFOLU sector CFP. The adoption of multispecies agroforestry systems with nitrogen-fixing trees is a promising strategy for accomplishing this goal. Another is integrated silvopastoral systems that combine animal production with deep-rooted grass and trees that could counteract the GHG emission through enteric fermentation in animals with enhanced soil C sequestration.

Keywords: AFOLU (Agriculture, forestry, and other forms of land-use), CO_{2eq} (agroforestry, carbon dioxide equivalent), GHG (climate change, Greenhouse gas), global warming potential

CLIMATE CHANGE AND GREENHOUSE GASES

Climate change, undoubtedly the most dominant discussion item in the global environmental agenda for

the past two to three decades, revolves around a single element, C (carbon). Carbon dioxide (CO_2) is its main atmospheric form and the metric - or currency - in which changes in atmospheric radiative forcing (i.e., global warming) are expressed. Other forms of C that are important from the environmental standpoint also exist, notably methane (CH_4). These gases, along with chlorofluorocarbons and nitrous oxide that are collectively called greenhouse gases (GHGs), contribute to the greenhouse effect leading to a rise in atmospheric temperature or global warming. The magnitude of all GHG emissions is expressed as the amount (tons) of CO_2 produced during a given period. Furthermore, the CO_2 concentration in the atmosphere - rather, its rapidly increasing levels during the past few decades - are the commonly quoted factor that preambles all discussions on climate change. The Mauna Loa station (of the National Oceanic and Atmospheric Administration, USA) records show that the atmospheric concentration of CO_2 increased dramatically during the industrial era, with the average decadal CO_2 increasing to 2.4 ppm (parts per million) per year during the 2010-2019 period compared to 2.0 ppm per year in the 2000s; the monthly average for January 2022 was 418 ppm *vs.* 415.5 ppm in January 2021.

GLOBAL EFFORTS IN COMBATING CLIMATE CHANGE

During the past four decades, massive global efforts have been undertaken by the United Nations and its specialized agencies with the involvement of the member countries to combat climate change. The setting up of the Intergovernmental Panel on Climate Change (IPCC) in 1988; the second Earth Summit at Rio de Janeiro, Brazil in 1992, following which 166 countries signed the United Nations Framework Convention on Climate Change (UNFCCC) that acknowledges humanity's role in global warming; the Conference of Parties (COP) every year that brings together all countries that have ratified the UNFCCC (197 as of 2021); the Kyoto Protocol adopted at the third COP in 1997 at Kyoto, Japan; the Paris Agreement at the COP 21 Summit in Paris in 2015; and the COP 26 Summit at Edinburgh, U.K., in 2021, are some of the landmark events and conferences in this series of global actions. Various countries and groups of countries have committed themselves (e.g., the "Green Deal 27" by the member states of the European Union) to achieving carbon neutrality by 2050, i.e., to ensure that the country/group of countries does not emit more greenhouse gases than it can absorb (known as "net-zero emissions"), targeting a 1.5 °C cap on the rise in standard temperature (Carbon Brief: COP26, Glasgow, 2021: (https://www.carbonbrief.org/cop26-key-outcomes-agreed-at-the-un-climate-talks-in-glasgow). The latest IPCC Report, 28 February 2022, gives a dire warning that humans must accelerate efforts to adapt to the challenges of a warming world and "any further delay in concerted anticipatory global action will miss a brief and rapidly closing window of opportunity to secure a livable and sustainable future for all" (https://www.ipcc.ch/2022/02/28/pr-wgii-ar6). Despite these commendable efforts, serious doubts persist as to how committed the countries concerned are in following up their words with appropriate deeds and fulfilling their avowed commitments. As noted above, the European Union has a clear strategy (the Green Deal 27) and financial commitment to adapt to climate change. On the other hand, in some powerful and large countries, for example, the United States, the response to climate change is a political issue; it is supported strongly by one side and opposed vehemently by the other. The number of climate-change deniers, however, has declined considerably during the past two decades and climate change continues to be a global issue of substantial public concern.

The literature on the topics surrounding climate change is unbelievably massive. Each major global summit involves enormous amounts of preparation with hundreds of delegations and meetings, each with voluminous background materials. For example, the latest IPCC Report released on 28 February 2022, referred to above, contains "a 3,700 page-long (a browser-freezing 280 megabytes) account of the state of the play regarding impacts, vulnerabilities, and adaptation." (*The Economist*, 5 March 2022). Then there are numerous scientific and academic publications, and hardly a day passes without a major news item or coverage about climate change in news media and popular press.

CARBON FOOTPRINT: THE CONCEPT

The concept of carbon footprint emerged gradually from the "ecological footprint" (EFP) concept of the 1990s; it was popularized by choosing the "area concept" (the global per capita area of productive land and water ecosystems required for the maintenance of the system) as its primary metric linked to the footprint metaphor[1]. The authors also explain how carbon footprints can be expressed in various ways: per unit product (e.g., of food, feed, fuel, or fiber) in a life cycle analysis, evaluating individual decisions on consumption and lifestyles, or the multifunctionality of land-use can be reflected in aggregated footprint metrics. Lal[2] (2022, this issue of the journal) identifies several sub-components of EFP including resource footprint (RFP) which comprises land (LFP), water (WFP), nitrogen (NFP), biodiversity (BFP), power (PFP), and carbon (CFP). Some might argue - sometimes in a belittling tone - that carbon footprint is just a new name for an old idea and another attention-grabbing entry in the long list of "fancy" terms. Whatever that be, today, CFP has emerged as the nexus for all the "GHG emission-global warming-climate change" discussions on the global environmental scene.

From this journal's perspective, carbon footprint (CFP) refers to the emissions of all GHGs and is expressed as the amount in tons (1 ton, t, called metric ton in the USA, equals 1 Mg or 10^6 g) of CO_2 produced during a given period (see Section 5 for more details). Although CFP encompasses major sectors of human activities such as land-use systems, energy, and transportation, the journal's focus is on the CFP of the broad agricultural sector or AFOLU (agriculture, forestry, and other forms of land-use)[3].

The early issues during the first year of the journal will feature scholarly articles (reviews, perspectives, and summaries) on the concept and philosophy of CFP, the extent of CFP in various forms of land-use systems in different geographical regions, the challenges involved in as well as approaches to gathering such information, the potential of the AFOLU sector in influencing CFP, and the opportunities for reducing or even reversing the CFP through some such land-management options.

ESTIMATES OF CARBON FOOTPRINTS OF LAND-USE SYSTEMS

Recent estimates (Nov 2021) by FAO, the UN Food and Agricultural Organization, show that 31% of human-caused GHG emissions originate from the world's agri-food systems. Of the 16.5 Pg (billion tons) of GHG emissions from global total agri-food systems in 2019, 7.2 Pg came from within the farm, 3.5 from land-use change, and 5.8 from supply-chain processes (New FAO analysis reveals carbon footprint of agri-food supply chain | | UN News, 9 Feb 2022). In 2019, deforestation was the largest source of GHG emissions, followed by livestock production (primarily from enteric fermentation), household consumption, food waste disposal, fossil fuels used on farms, and the food retail sector. The FAO maintains that the food supply chain in many countries is on course to overtake farming and land-use as the largest contributor to GHG from the agri-food system. Moreover, unrelated farm activities and land-use changes currently account for more than half of the CO_2produced from agri-food systems in some regions while in developing countries over the past three decades, it has more than doubled. The U.S. Environmental Protection Agency estimates that currently agriculture and forestry together account for 10.5% of the US GHG emissions (0.7 Gg = MMT or million metric tons), while transportation and industry are estimated to account for about 60% of emissions or 4.0 Gg[4].

While such large datasets present the seriousness of the issue at the global or regional scale, they do not show the extent of variations that exist among different regions and within the regions. Authoritative perspectives on the CFP status of some major land-use systems in a few large countries/regions of the world are presented in the early issues of the journal. These include the scenario for the agriculture sector in Brazil[5], forestry and agroforestry sectors in the United States[4], and the AFOLU sector in India[6].

Additional accounts of CFP status under land-use systems in some other regions such as southern Africa and Europe will be included in subsequent issues of the journal this year (2022); these are still under preparation and are therefore not referenced here.

Gama-Rodrigues *et al.*[5] present an analysis of the status of GHG emissions and CFP in Brazil, one of the main producers in the agricultural and forestry sector worldwide. The main sources of national GHG emissions in Brazil are beef cattle (due to enteric fermentation) and the management of agricultural soils (primarily the use of nitrogen fertilizers). The increasing adoption of low-carbon agriculture has led to a reduction in the carbon footprint through no-till technologies, agrosilvopastoral systems, the use of N_2 fixing plants, and the expansion of planted forests. The authors recommend that these technologies deserve to be increasingly disseminated to generate economic opportunities leading to financial gains from the commercialization of carbon credits and payment for environmental services.

Discussing the role of major land-use systems in carbon footprint discussions with special reference to the USA, Udawatta and Jose[4] emphasize the role of forests, grazing lands, and croplands. Forests that cover 4.06 billion ha or 31% of the global land area[7] have a major role in both emitting and storing carbon worldwide. The net of emissions and storage, known as C flux, is expressed usually in tons (or million metric tons, MMT, in the US) of CO_2. In addition to the movement of C in and out of the forest, there is also storage of C in different "compartments" of the forest system referred to as C stock. The IPCC recognizes five such storage pools in the forest ecosystem[8]: aboveground biomass, belowground biomass, deadwood, litter, and soil C, and the FAO assumptions are 45% C stock in soil organic matter, 44% in living biomass, 6% in the litter, and 4% in deadwood[7]. In the US, pastureland and rangeland occupy 49.2 and 163.4 Mha and account for 6% and 21% of the total land area[9]. Among the various agroforestry practices, silvopasture is recognized to have the greatest potential to sequester C in temperate North America, but the exact land area under silvopasture is not known. Udawatta and Jose[4] estimate that, in the U.S., 248 Mha of permanent pastures/range, 51 Mha of grazed forests, and 40 Mha of unmanaged forests may offer the potential for conversion to silvopasture; the authors visualize that such conversions could not only improve C accrual but provide various other ecosystem services too. On croplands in the US that cover 149 Mha[9], the carbon sequestration ranges from 0.13 Mg ha^{-1} yr^{-1} with no C sequestration management to 0.5 Mg ha^{-1} yr^{-1} with C sequestration management[10].

Reviewing the scenario of CFP in India, Kumar and Aravindakshan[6] report that the AFOLU sector contributes 7%-8% of the total CO_2 emissions nationally, which is considerably lower than the global estimate of 25% as the sector's contribution to total emissions, and this has raised the country's aspirations of reaching net-zero emission by 2070. The authors identify enteric fermentation, fertilizer and manure management, rice paddies, burning of crop residues, forest fires, shifting cultivation, and food wastage as the major CFP issues of the AFOLU sector in India. Further, they project that the emission pathways of the AFOLU sector for 2070 can be leveraged proactively to reach the net-zero emission goals by focusing on increasing forest cover, agroforestry, and other tree-based land-use systems, improving soil health through soil management, and better crop residue and livestock feed management.

Numerous other reports on CFP values of various land-use systems from different situations are also available. Despite the limitations and conditions of the studies concerned, the main point that emerges from these reports is that the CFP levels of commercialized and heavily fertilized monocultural stands of crops and trees are much higher than those of mixed-species stands, especially those involving N_2-fixing species and environment-friendly land-management practices. Combined production systems such as various types of agroforestry practices and other forms of conservation agriculture are frequently reported as highly

desirable too. Understanding the magnitude of CFP of land-use systems and factors affecting it can lead to the identification of technological options that can enhance the use efficiency of inputs, reduce wastage, and decrease the CFP.

It is worth mentioning in this context that the CFP is not synonymous with the impacts of climate change or global warming. As stated before, CFP is a measure or indicator of the total emissions of all GHGs by an entity or activity. High levels of CFP lead to an increase in global warming that could have various adverse impacts on the AFOLU and other sectors and the overall environment: sea-level rise, increased frequency of anomalies such as droughts, floods, and forest fire, biodiversity changes above- and belowground, and so on. From the agricultural and land-use perspective, even relatively small changes (1 ^{o}C to 2 ^{o}C) in atmospheric temperature could lead to serious effects on the growth and performance of some temperature-sensitive crops. For example, the world-renowned arabica coffee (*Coffea arabica*) in the East African highlands of Kenya and Ethiopia is being replaced by the less preferred robusta coffee (*Coffea canephora*) that can withstand higher temperature than the arabica coffee. Even such modest changes in temperatures could also cause a significant increase in the incidence of pests and diseases that damage these crops. The shaded perennial agroforestry systems where shade- adapted crops such as coffee and cacao (*Theobroma cacao*) could conveniently be grown with reduced exposure to direct sun and higher temperature are alternative approaches to withstand such climatic situations (Nair *et al.*[11]2021, Chapter 8). Another example of the effect of climate change is the huge dieback of largescale forest plantations of Norway spruce (*Picea abies*) in Central Germany, where "scientific" monocultural forestry has originated and been successfully practiced for three centuries (*Science* 374, issue 6572, 1184 - 1189, 3 December 2021.

MEASUREMENT AND ESTIMATION OF CARBON FOOTPRINT

It is customary to mention numerical values of CFP and global warming potential for every activity or practice that is mentioned in reports related to climate change and the environment. The standard unit for CFP is the carbon dioxide equivalent (CO_{2eq}) expressed as parts per million by volume, and the impact of each greenhouse gas is expressed in terms of the amount of CO_2that would create the same amount of warming. Thus, a CFP consisting of different GHGs can be expressed as a single number. Standard ratios are used to convert the various gases into equivalent amounts of CO_2. These ratios are based on the so-called Global Warming Potential (GWP) of each gas, which describes its total warming impact relative to CO_2over a set period (or "time horizon," usually 100 years). Over this time frame, according to the standard data, methane has a score of 25 (meaning that one ton of methane will cause the same amount of warming as 25 tons of CO_2), nitrous oxide has a score of 298. The choice of a time horizon is a critical element in the definition. A gas that is quickly removed from the atmosphere may initially have a large effect and become less important over longer periods as it gets removed. Methane, for example, has a warming potential of 25 over 100 years, but 72 over 20 years. Therefore, the impact of methane and the strategic importance of tackling its sources depends on whether we are more interested in the next few decades or the next few centuries. The 100-year time horizon set by the Kyoto Protocol puts more emphasis on near-term climate fluctuations caused by emissions of short-lived species (like methane) than by emissions of long-lived GHGs. The GWP value depends on how the gas concentration decays over time in the atmosphere, and since this is often not precisely known, the values are not considered exact. Nevertheless, the concept of the GWP is generally accepted as a simple tool to rank emissions of different GHGs. Carbon footprint values are also expressed on an annual, per capita basis for different countries and regions. The values (Mg CO_{2eq} /person/year) for 2020 listed by Lal[2] range from as low as 0.1 in Niger to 18.58 in Canada, with a global average of 4.48. In general, however, the global averages of indicators related to human well-being and prosperity are projected mostly as symbolic gestures and, understandably, they keep changing. The current (early 2022) standards are that for attaining the goal of limiting global warming to 20C, the global average

per capita CFP of humanity may be reduced to < 2 Mg CO_{2eq}.

The standards and datasets on CFP, GWP, and related terms are usually computed or estimated for a location or region, except in focused experiments, based on the recommendations and instructions from international entities such as IPCC and the national and regional bodies. For example, the IPCC recommends that enteric emission estimates in Brazil can be made with a simplified procedure, using the average data of Latin America[12] that ranges from 56 (Tier 1) to 70 kg CH_4 animal^{-1} y^{-1} (Tier 2), but regional and specific emission factors should be used when available. Moreover, different methodologies exist for estimating the values for the whole systems or their parts, as well as for the whole lifecycle or specific segments of the life cycle. Therefore, the CFP values reported for various systems can vary considerably: see, for example, papers in this volume by Lal[2], and country-specific reports by Gama-Rodrigues *et al.*[5] for Brazil, and Udawatta and Jose[4] for North America.

Methods for measurement and computation of C sequestration in terrestrial systems are still uncertain (see Chapter 20, Nair *et al.*[11], 2022). Modeling soil carbon using artificial intelligence (AI) - machine learning and deep learning algorithms - has emerged as a powerful force in the carbon science community. Reviewing the recent developments in these exciting areas, Grunwald[13] reported that these AI soil carbon models have shown improved performance to predict soil organic carbon, soil respiration, and other properties of the global carbon cycle when compared to other modeling approaches.

LAND-MANAGEMENT OPTIONS FOR REDUCING CFP

The rapidly swelling literature on CFP emphasizes the dominant impact of agriculture on CFP and prescribes land-management options for reducing it as exemplified in the CFP status reports from a few large countries/regions presented in this issue of the journal. As mentioned earlier, all segments of the food and agricultural sector related to the production, processing, transportation, and storage, as well as preparation of food and disposal of food wastage, have negative CFP impacts to varying degrees. The most significant and indelible footprints, however, are caused by the soil application of chemicals such as fertilizers, weedicides, and insecticides; some reports suggest that the application of nitrogen fertilizers to crops alone is responsible for 75% of total emissions[2]. Burning of cereal crop residues in the grain belt of India is a traditional practice that has been widely recognized - indeed dramatized as "Fields on Fire"[14] - as a major source of carbon emission and environmental pollution causing serious consequences.

Compared with the other major sectors, however, the AFOLU sector has the unique potential to remove CO_2 from the atmosphere and sequester it in soil via appropriate land management measures. These include reduced tillage operations (minimum tillage), reduced chemical inputs (including fertilizers, herbicides, and insecticides), and the adoption of appropriate farming systems such as agroforestry to enhance photosynthetic carbon capture. Many of these issues are described in detail in the authoritative papers that follow in the early issues of this journal.

One of the widely recognized approaches to reducing CFP of agriculture and land-use is to enhance terrestrial sequestration of carbon. This can be accomplished by promoting the natural process of C sequestration in soil and vegetation such that atmospheric CO_2 is removed via photosynthesis and stored in the biomass and soils of terrestrial ecosystems for extended periods (> 100 years). Some ecosystems, such as the grasslands, are well known for their ability to store high amounts of soil organic C because of the deep root systems of grasses as well as their resilience to rising temperatures, drought, and fire, such that the sequestered terrestrial C is stored in belowground sinks and prevented from re-entering the atmosphere (https://www.fs.usda.gov/ccrc/topics/grassland-carbon-management). At the same time, frequent

occurrences of devastating forest-and-grassland fires around the world, often portrayed as caused and exacerbated by unmitigated climate change, turn these substantial C sink ecosystems into major C sources. Alternative land management options such as silvopastoral and other forms of agroforestry systems[15] are being tried to maintain such climate-vulnerable forests and grasslands as C sinks and avoid the risk of them becoming C-emitters.

The concept of agroforestry is based on traditional experience supported by modern scientific evidence about the proven role of on-farm and off-farm tree production in supporting sustainable land-use and natural resource management. While the aboveground and belowground diversity provides more stability and resilience for the system at the site level, the system provides connectivity with forests and other landscape features at the landscape and watershed levels[14,15]. These ecological foundations of agroforestry systems manifest themselves in providing environmental services such as soil conservation, carbon storage, biodiversity conservation, and enhancement of water quality, all of which are directly related to the concept of CFP. Silvopastoral and other agroforestry management options are widely acknowledged to offer enormous possibilities in this direction (Nair *et al.*[11]2021, Chapter 20).

CONCLUSIONS

A common adage that is attributed to Albert Einstein reads *"The significant problems we face today cannot be solved at the same level of thinking we were at when we created them.* It is very true today in the context of the global enthusiasm and efforts in addressing the issue of carbon footprints, and it is an issue of relevance to all humanity. The adverse impacts of increasing carbon levels in the atmosphere and the recognized impacts of human activities on carbon emissions, i.e., carbon footprint, are of considerable importance to all. Concerted efforts are being undertaken by the global community at all levels to address this threat of an apocalyptic nature. Certainly, the land-use-systems community at every level, from farmers and other land-users to scientific professionals, administrators, and policymakers, ought to be committed fully to addressing this issue of gargantuan proportions. The launch of this new scientific journal, *Carbon Footprints*, is a tiny part of that massive effort, and we are enthusiastically looking forward to the opportunity for making our humble contributions to the fight against climate change and global warming.

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The author contributed solely to the article.

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Carbon Footprints

Original Article

Open Access

Reducing carbon footprints of agriculture and food systems

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Abstract

Increase in global populations of humans and domesticated livestock are impacting the resource use and have a large ecological footprint (EFP). The ever-increasing EFP of humanity is accelerating climate change, increasing water scarcity and contamination, aggravating soil degradation, and dwindling above and below-ground biodiversity. Several sub-components of EFP include resource footprint (RFP) which comprises land (LFP), water (WFP), nitrogen (NFP), biodiversity (BFP) power (PFP), carbon (CFP), *etc.* Agricultural practices (e.g., tillage, fertilizer and pesticide use, farm operations such as irrigation, harvesting, baling, *etc.*) also cause the emission of greenhouse gases (GHGs) such as CO_2, CH_4, and N_2O, and these gasses equivalent in their global warming potential (GWP). In general, CFP is reported as CO_{2eq} by converting CH_4 and N_2O into CO_2. The Human diet, consisting of plant and/or animal-based products and grown diversely with or without chemicals, irrigation, and modern innovations, has a wide range of EFP. The latter, is the widely used measure of resource consumption and humanity's impact on the planet. EFP encompasses the cumulative GHG emissions by an individual, community, organization, institution, nation for a specific service or product. It can vary widely because of using different reference systems of the studies and differences in system boundaries. Therefore, standardization of the methodologies may require a better understanding of the various ways related CFP concepts are relevant for decisions at individual to global levels. There is no one size that fits all. It is also widely recognized that the global average per capita CFP of humanity, estimated at 4.47 Mg CO_{2eq} in 2020 is not sustainable, and must be reduced to < 2 Mg CO_{2eq} if the global warming is to be limited to 2 ^{0}C. Therefore, understanding the magnitude of CFP of agriculture and food systems (FSs), and factors affecting it, can lead to identification of technological options which can enhance the use efficiency of inputs, reduce wastage, and decrease the CFP. Different FSs affect CFP through diverse components of production and supply chains, and in the manner in which food is stored and cooked and the

waste is disposed or recycled. There is need to adopt international standard (ISO) protocol. Therefore, this review identifies and deliberates technological options which may be needed for reducing CFP of humanity in general but that of agriculture and FSs in particular, while also advancing Sustainable Development Goals of the Agenda 2030 of the United Nations. CFP of diverse agro-ecosystems, land use and management systems are also discussed. Specific examples of CFP include type of farming systems (organic *vs.*. conventional, dietary preferences, and food waste). There are several options for the humanity to change lifestyle and make it more sustainable. Food waste, about one-third of all, is an important factor impacting CFP while also accelerating global warming. The impact of avoidable food waste on gaseous emissions, estimated at 2.0 to 3.6 Mg CO_{2eq} per Mg of food waste on dry weight basis, must be minimized.

Keywords: Global emissions, environmental footprint, ecological footprint, carbon footprint, global warming, soil carbon sequestration, greenhouse gases

INTRODUCTION

Anthropogenic warming of the planet is among serious global issues of the 21st Century. The present civilization since c 1750 is appropriately called the "Carbon Civilization"(Lal[1], 2007), because of its dependence on fossil C as a source of energy. Since the onset of Industrial Era c 1750, total anthropogenic emissions are estimated at ~690 Pg of carbon (C), two-third of which came from fossil fuel combustion and one-third from land use change [Table 1]. However, ~30% of the anthropogenic emissions have been and are absorbed by the land-based sinks and another 25% by the ocean [Table 1]. Absorption by natural sinks raises the issue of net *vs.* gross emissions as basis for human accountability, as well as responsibility for predicted sink saturation and sink decline due to anthropogenic activities. Indeed, the 4 per 1000 initiative launched at COP21 in Paris in 2015 was based on the net emissions [Table 1]. Yet, agriculture contributes about 14% (Grünberg *et al.*[2], 2010) and food systems (FSs) about one-third of anthropogenic greenhouse gas (GHG) emissions (IPCC 2019; Balogh[3,4] 2019). Emission of GHGs from agriculture and FSs is increasing because of an ever growing and progressively affluent human population. Success of the Green Revolution technology since the second half of the 20th Century came at a cost of a significant ecological/environmental footprint or EFP (Khan and Hanjra[5], 2009). Increase in global population at the rate of about 1% per year, from 7.95 B in February 2022 to 9.7 B in 2050 and 11B in 2100 (U.N., 2019)[6], is worrisome in terms of its EFP. In the context of Sustainable Development Goal (SDG) #2 of achieving Zero Hunger by 2030, 691 M were food-insecure in December 2019 prior to COVID Pandemic and the number increased to 820 M by December 2020 (FAO and UNICEF and WHO, 2021)[7]. It is widely argued that SDG #2 will not be realized by 2030. Indeed, global food insecurity is a complex problem. Some perceive the problem as not enough food and argue about the need to increase supply, while others believe the need for reducing consumption and avoiding food waste and emphasizing the need to shift diets. It is apparent, therefore, that achieving worlds sustainable FSs will necessitate simultaneous action on many fronts; improved supply of nutritious food and reduced demand and waste (Röös *et al.*[8], 2017; Fanzo *et al.*[9], 2021; von Braun *et al* [10], 2021). Thus, there is a strong need to reduce the environmental impact by reducing GHG emissions from agriculture and FSs and by re-carbonization of the terrestrial biosphere. Yes, reducing environmental impact by improving agriculture and transforming FSs are among the highest priorities for limiting global warming to 2 °C, and advancing SDGs of the Agenda 2030 of the U.N. (U.N., 2015; Lal *et al.*[11,12], 2021). Therefore, the objectives of this article are: (1) to review the degree to which various foot prints reflect the key issues and response options; and (2) using CFP concepts, review priorities for action at various levels of decision-making.

Table 1. Historic carbon emission from land use and fossil fuel emissions (recalculated from Friedlingstein *et al.*[82] (2021)

Source/Sink		PgC			
		1750-2020	1850-2021	1960-2020	2021
I Source					
	Land Use Change	235 ± 75	205 ± 65	80 ± 45	9.7 ± 0.5
	Fossil Fuel	460 ± 25	465 ± 65	375 ± 20	0.8 ± 0.7
	Total	690 ± 80	670 ± 65	455 ± 45	10.5 ± 0.9
II Sink					
	Atmosphere	290 ± 5	270 ± 5	205 ± 5	4.2 ± 0.4
	Ocean	180 ± 35	170 ± 35	115 ± 25	2.9 ± 0.4
	Land	215 ± 50	200 ± 45	135 ± 25	3.3 ± 1
	Imbalance	10	25	0	0.1
Land/Sink (% of total source)		31.1	29.9	29.8	31.4

INDICATORS OF ENVIRONMENTAL FOOTPRINT

Pertinent indicators of environmental impact of agriculture and FSs are parameters that reflect the direct and indirect measures of resource consumption and adverse changes in quality and functionality of finite, critical and fragile natural resources. Some important among these ecological indicators are quality of soil, water, atmosphere or air, and biodiversity. Rather than being considered as factors of production, natural resources can be considered as finite, fragile and non-renewable. Wiek & Tkacz[13] (2013) proposed the concept of "ecological indicator" or EFP based on life cycle analysis for a wide range of products and services, to signify ecological assets that a community needs and the natural resources it uses to produce the essential goods and services and to absorb or dispose the waste or by-product. In relation to global warming and anthropogenic emissions, therefore, EFP, comprising of all components including water and biodiversity, is an indicator of GHG emissions in production of goods or services. This indicator, converted to a carbon (C) equivalent for product and services for the entire life cycle from the cradle to grave is called "carbon footprint" or CFP. The latter is a widely used in the public domain to address the threat of anthropogenic climate change (Chen *et al.*[14], 2021). CFP, being the main component of EFP, may represent more than 50% of the total EFP of an agricultural product (Balogh[4], 2019). However, the EFP comprises of a range of components such as land (LFP), water (WFP), biodiversity (BFP), nitrogen (NFP), food (FFP), resources (RFP) *etc.* [Figure 1]. The term CFP refers to a collective numerical value of all components of EFP (e.g, LFP, WFP, BFP, RFP, FFP *etc.*) reported in terms of carbon dioxide equivalent (CO_{2eq}). Thus, CFP is widely used in the context of global climate change and identification of options for its mitigation and adaptation.

Understanding the magnitude of CFP of agriculture and FSs, and factors affecting it, can lead to identification of technological options which can enhance the use efficiency of inputs, reduce wastage, and decrease the CFP.

The CFP includes total amount of all GHGs, including carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O), emitted by an activity (e.g., agriculture, transport, landfill of waste) [Figure 2]. Specifically, CFP encompasses the cumulative GHG emissions and there are different ways of expressing CFP such as at level of an individual, community, organization, institution, or service. Principal sources of GHGs from agriculture are N_2O from soils through inputs of inorganic fertilizer and organic amendments (i.e., compost, manure, biological nitrogen fixation), CH_4 from enteric fermentation in ruminants and emission from rice paddies (Röös *et al.*[15], 2014) and CO_2 from land use conversion (e.g., deforestation, and diesel consumption in farm operation) including tillage and drainage of wetlands for cultivation of upland crops. Assessing the

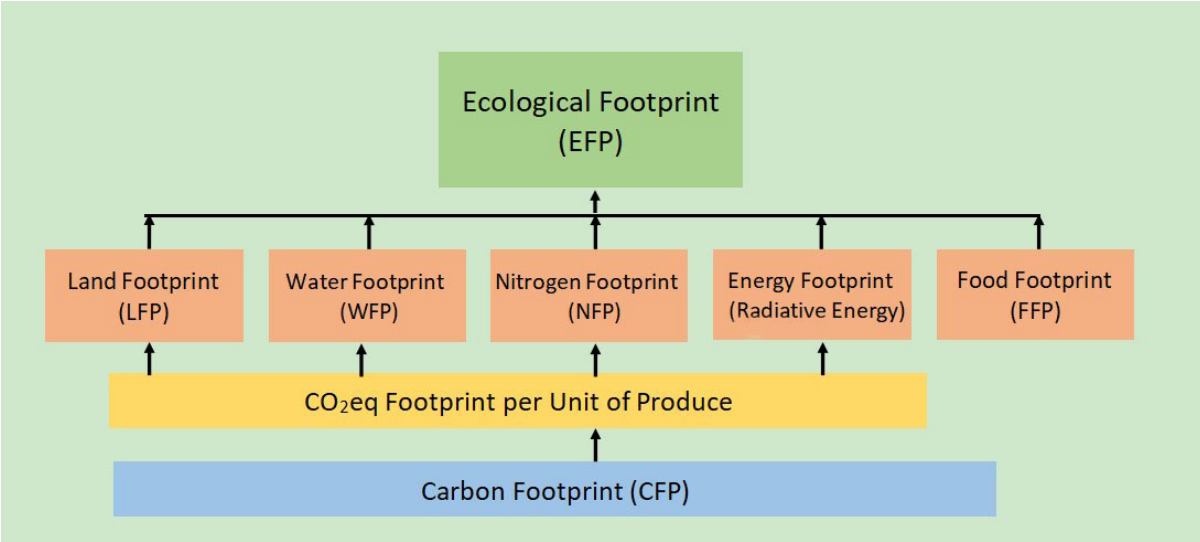

Figure 1. Components of ecological footprint.

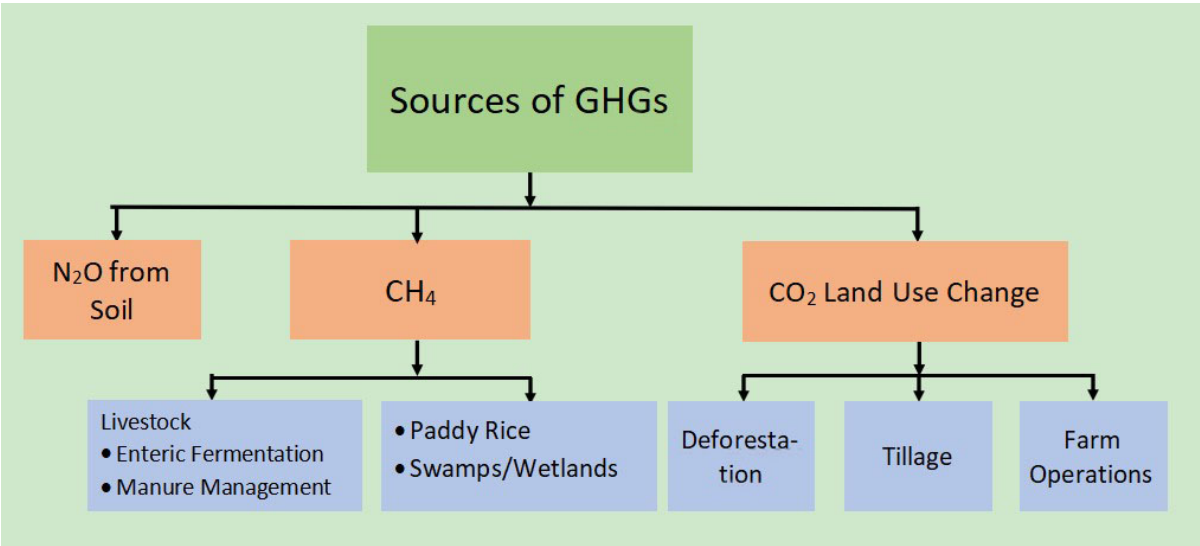

Figure 2. Carbon footprint of food products.

impact of agricultural drainage on increasing emissions of adjacent forest is a challenging issue which needs to be addressed. Because the radiative-forcing or the global warming potential (GWP) of CH_4 and of N_2O is higher than that of CO_2, appropriate factors are used to convert emissions of all GHGs to CO_{2eq} depending upon an agreed timeframe (IPCC, 1996)[16].The GWP is a measure of the relative, globally-averaged warming effect arising from the emissions of a particular GHG [Table 2].

Agricultural practices (e.g., tillage, fertilizer and pesticide use, farm operations, irrigation, harvesting, bailing *etc.*) have different emission of CO_{2eq} (Lal[17], 2004). Similarly, crop production and animal raising differ in their GWP. Drainage and cultivation of peatland is the major cause of emission of GHGs. The calculated GHG emissions of farm products, place or an activity over a specified period is needed to compute CFP. In general, CFP is reported in the units of Kg CO_{2eq} by converting CH_4 and N_2O into CO_{2eq}uivalent.

Table 2. Global warming potential of 3GHGs for different time horizons (adopted from (Ramaswamy *et al.*[83],2001)

	Time Horizon (Yr)		
Gas	20	100	500
CO_2	1	1	1
CH_4	62	23	7
N_2O	275	296	156
CFC_{11}	6300	4600	1600
CFC_{12}	10,200	10,600	5200
$HCFC_{21}$	700	210	65
$HCFC_{22}$	4800	1700	540

CFP can vary widely because of using different reference systems of the studies and differences in system boundaries (Grünberg *et al.*[2], 2010). Therefore, standardization of the methodologies following the international Standard (ISO) is critical to obtaining credible information for making sound decisions. Thus, a wide range of CFP reported in the literature for the same product or service may be attributed to differences in the complete or some parts of the value chain rather than that for the whole life cycle. Choosing a different baseline, and different emission factors can also lead to differences in CFP for the same product or service (Grünberg *et al.*[2], 2010).

PER CAPITA EMISSIONS

The global annual average per capita CFP differ among countries based on their economic development and lifestyle. The national average per capita CFP (Mg CO_{2eq}) varies widely and in 2020 is estimated at 15.52 for USA, 7.38 for China and 1.91 for India with corresponding population of 323 million, 1.41 billion and 1.35 billion, respectively [Table 3]. The national average per capita CFP is higher for developed than developing nations. The lowest per capita CFP at present is for countries in Sub-Saharan Africa followed by those in South Asia [Table 3]. The global per capita CFP (Mg CO_{2eq}) was 3.1 in 1960, 4.1 in 1970, 4.6 in 1980, 3.9 in 1990, 3.8 in 2000, 4.48 in 2010 and 4.48 in 2020 [Table 4], (World Bank, 2019)[18]. Tiseo[19] (2021) reported that global average per capita CO_2 emission dropped by about 7% in 2020 because of the disruptions by COVID pandemic. There is also large variation in per capita CO_2 emission among G20 nations. For 2020, per capita CO_2 emissions (Mg CO_2/person. Yr.) in G20 countries in descending order was Saudi Arabia (16.76), Australia (15.21),Canada (14.43), USA (13.68), South Korea (12.06), Russia (11.64), Japan (8.39), China (8.19), Germany (7.71), South Africa (7.41), Italy (5.03), Turkey (4.83), United Kingdom (4.66), France (4.26), Argentina (3.87), Mexico (3.04), Brazil (2.11), Indonesia (2.08) and India (1.74) (Statista.com). Countries with the highest per capita CO_2 emissions are Qatar (30.7), Kuwait (21.3), Gibraltar (21.1) and Bahrain (19.9).However, the global average per capita CFP of 4.47 Mg CO_{2eq} in 2020 must be reduced to < 2 Mg CO_{2eq} by 2050 if the global warming is to be limited to 2 ^{o}C.

IMPORTANCE OF AGRICULTURE AND FOOD SYSTEMS IN CARBON FOOTPRINT

It is widely recognized that the present EFP of humanity is not sustainable. Through land use conversion for agriculture and other anthropogenic activities, humanity has altered planetary processes by strongly transforming the earth's landscape, drastically increasing the resource use and generating a huge amount of waste. Hoekstra & Wiedmann[20] (2014) observed that actual versus sustainable EFP of humanity was 18.2 *vs.* 12 B ha of land, 46-55 *vs.*18-25 Gt of CO_{2eq}. per year, 1000-1700 *vs.* 1100-4500 B m^3 of blue water, and 10.5 *vs.* 8.0 Mg/capita of material foot print. Hoekstra and Wiedmann also observed that humanity's WFP (B m^3 per year) was 6700 for green water and 1400 for gray water. Food and agriculture are the vital components of human wellbeing and the heart of civilization that began with the onset of agriculture about 8000 BC. Most religions and cultures celebrate agriculture and soil as a part of their heritage (Lal[21], 2013). Indeed,

Table 3. Comparison of carbon foot print (Mg CO_{2eq}/person/year) of 25 countries in sub-Saharan Africa, South and Central Asia, Americas-Europe (adapted from Worldometer, 2022)[84]

Carbon Footprint (Mg CO_{2eq}/person/yr)					
Sub-Saharan Africa		**Developing and developed Asia**		**Europe and Americas**	
Zimbabwe	0.72	Turkmenistan	14.0	Canada	18.58
Benin	0.60	Kazakhstan	13.01	Australia	17.1
Senegal	0.55	South Korea	11.85	USA	15.52
Ghana	0.51	Taiwan	11.72	Russia	11.44
Nigeria	0.44	Japan	9.70	Netherland	9.62
Ivory Coast	0.42	Malaysia	8.66	Germany	9.44
Cameron	0.40	Singapore	8.56	Finland	9.31
Kenya	0.33	China	8.19	Austria	8.43
Sudan	0.33	Iran	8.08	Belgium	8.34
Togo	0.31	Hong Kong	6.50	Ireland	8.32
Mozambique	0.21	Thailand	3.93	Norway	8.28
Tanzania	0.18	Uzbekistan	3.68	Poland	7.80
Liberia	0.18	Azerbaijan	3.50	Denmark	6.65
Sierra Leone	0.17	Bhutan	2.28	Italy	5.90
Uganda	0.13	Vietnam	2.20	Venezuela	5.89
Bukina Faso	0.13	Indonesia	2.03	U.K.	5.58
Madagascar	0.12	India	1.91	Spain	5.40
Rwand	0.12	Philippines	1.22	Hungry	5.23
Malawi	0.11	Kyrgyzstan	1.14	France	5.13
Chael	0.11	Sri Lanka	0.88	Switzerland	4.73
Ethiopia	0.10	Pakistan	0.87	Serbia	4.65
Nigel	0.10	Tajikistan	0.70	Argentina	4.61
Mali	0.09	Bangladesh	0.47	Sweden	4.54
Somalia	0.09	Cambodia	0.41	Mexico	3.58
DR Congo	0.08	Myanmar	0.31	Brazil	2.25
		Nepal	0.29		
		Afghanistan	0.28		

Table 4. Temporal Changes in Global per Capita CO_2Emissions (Mg CO_2/Person (year) between 1960 and 2020 (World Bank, 2019, Tiseo, 2021)[18,19]

Year	World bank	Statista.com
1960	3.12	3.05
1965	3.43	3.39
1970	4.15	4.03
1975	4.34	4.18
1980	4.60	4.37
1985	4.43	4.17
1990	3.90	4.27
1995	3.78	4.08
2000	3.81	4.11
2005	4.20	4.53
2010	4.48	4.79
2015	4.48	4.81
2018	4.48	4.80
2020	4.47	4.47 (COVID)

sustainable management of soil and agriculture are critical to achieving world peace and stability (Lal[22], 2015). Agriculture and FSs are also major consumer of natural resources. Presently, more than 40% of the ice-free land is used for agriculture accounting for 3.75 B ha allocated for raising animals and 1.5 B ha for growing crops. Further, 70% of all fresh water withdraw is used for irrigation. Despite being an issue that is the heart of humanity, as documented by diverse religions and cultures (Lal[21], 2013; Lal[22], 2015), agriculture and FSs also have their ugly side (hunger and malnutrition) which must be addressed. The latter involves perpetuation of hunger and hidden hunger and adverse impacts of agriculture and FSs on environment (e.g., soil, water, air and biodiversity).

FSs are complex and all-inclusive. The first step of FSs, growing crops and raising livestock, involves agriculture, horticulture, forestry and fishery. In addition to growing food, other components of the FSs are transporting, processing, distributing, using, preparing, consuming and disposing of the food waste. The present FSs have severe limitations such as failing to end hunger and malnutrition, not being able to provide adequate amount of safe and nutritious food to all people, and being responsible for degrading soils, polluting water, aggravating global warming, dwindling biodiversity and denuding the landscape. Indeed, one-third of all soils are degraded (FAO & ITPS, 2015; IPBES, 2019)[23,24]. Furthermore, emissions from FSs (production and supply chains) account for 25%-30% of all anthropogenic emissions (IPCC, 2019)[3], and are increasing at the rate of 1% per year. Yet, prevalence of undernutrition affects 820 million and that of malnutrition 2 billion people, and the ever increasing number of soil and climate refugees is threatening the global peace and stability (Lal[22], 2015). Above all, the problem of inadequacy of FSs has been aggravated through the disruptions in all components (both production and supply chain) caused by the COVID pandemics (Lal *et al.*[25], 2020).

Being a major source of biomass for human needs, agriculture is a major factor affecting per capita national [Table 3] and global [Table 4] CFP. Weinzettel *et al.*[26] (2019) evaluated potential net primary productivity (NPPpot) of 186 agricultural crops in 236 countries, and found that human society appropriate 20% (13 Pg C) of global NPP, which may increase with growing and increasingly affluent world population.

Of the total CFP, agriculture and FSs constitute a large component, especially in developing countries [Table 3]. COP-26 in Glasgow (2021) identified five pillars to reduce CFP: (1) end waste; (2) use electricity prudently; (3) adopt bioenergy for circular economy; (4) use hydrogen; and (5) sequester carbon (C). The last pillar of C sequestration is important to agro-ecosystems, most of which are strongly depleted of their terrestrial C reserves (Lal[27], 2018), and have a large potential to sequester atmospheric CO_2 in biomass (trees, forests, woodlands) and soil (Lal *et al.*[28], 2018). Sequestration of atmospheric CO_2 in agroecosystems is an important option to reduce humanity's CFP.A wide range of agricultural factors play an important role in CFP of agriculture production. Balogh[4] (2019) argued that CFP of agriculture depends on economic development and agricultural production such as arable land, agricultural machinery, fertilizer use, irrigation, and other inputs. Therefore, the strategy of reducing CFP of FSs is to identify factors affecting productivity and use-efficiency of agriculture, and to identify site-specific technological options, based on recommended and science-based proven practices, which can reduce the CFP of food products and other related commodities.

FACTORS AFFECTING CFP OF AGRICULTURE

The global FSs vary widely from production of chemicals (e.g., fertilizers, pesticides) and seed to food packaging, and diverse agronomic systems such as with or without tillage, irrigation, chemicals, residue retention, and genetically modified organisms (Lal[17], 2004a). Fertilizer use has drastically increased in Asia and Latin America. Total and rate of fertilizer use in India from 1950 to 2020 in Table 5 indicate drastic

Table 5. Fertilizer ($N + P_2O_5 + K_2O$) use in India and the world (FAO, 2021)[85]

Year	Total (Mt/yr)		Rate (kg/ha)		India as % of World	
	India	World	India	World	Total	Rate
1950	0.069	-	0.49	-	-	-
1960	0.294	30.9	1.93	30.85	0.95	6.26
1970	2.257	68.61	13.61	68.61	3.29	19.84
1980	5.517	115.79	31.95	115.79	4.76	27.59
1990	12.539	136.95	67.55	136.95	9.16	49.32
2000	16.702	134.75	90.12	134.75	12.39	66.88
2010	28.124	173.76	141.93	173.76	16.18	81.88
2015	25.58	184.01	135.76	186.02	13.90	73.00
2018	27.2	194.39	160.8	120.9	14.5	133.0
2019	29.4	198.10	173.5	122.9	15.4	141.2
2020	32.512	201.66	161.01	188.52	16.1	85.4

The data in this Table was collated with the help of IFDC, Muscle Schoals, AL.

increase. Similar trends are observed in China, Brazil and elsewhere in emerging economies. Thus, treating soil as a factor of production or a finite resource, and crop residues as a resource or waste can make a strong difference in CFP. Developing methods for credible estimation of the CFP is important to identifying policies for promoting those food/agricultural systems which have low and discouraging those which have a high CFP. Such understanding is critical to making the environment-friendly choices in lifestyle of a community, region or a nation. Components of the life cycle analysis for FSs may include raw material acquisition (e.g., land, chemicals, energy for farm operations, irrigation water lift and application), processing, packaging, storage, transportation, consumption, along with disposal of food waste (Xu *et al.*[29], 2015). The CFP can be computed on the basis of footprint weight, sustainability measures, and % daily value (Leach *et al.*[30], 2016). It comprises of direct and indirect emissions of GHGs. Direct emissions are those GHGs which are released at each step of the process and indirect are CO_{2eq} emissions caused by energy consumption in each process (Wu *et al.*[31], 2013). Identification and quantification of these components of CFP, outlined in Figure 1, is essential to developing strategies of optimizing the CFP. Thus, there is a need to develop methodology that permits assessment of foot print of diverse entities (e.g., water, biodiversity) into common units. Assessing footprint of each component is essential to developing strategies of reducing CFP and advancing practices which lead to sustainable development based on ecological principles of production and consumption.

CARBON SEQUESTRATION FOR REDUCING CFP OF A PRODUCT OR SERVICE

Carbon capture and storage (CCS) in soil and vegetation is called terrestrial sequestration. CCS in terrestrial ecosystems is a natural process and is based on the removal of atmospheric CO_2 by photosynthesis and retention of biomass-C in soil and vegetation so that it is not re-emitted into the atmosphere but is retained in the terrestrial ecosystems for a longtime. In this context, a primary goal of sustainable systems of soil, crop, tree and livestock management is to protect, restore and manage the terrestrial C stocks so as to enhance or prolong their mean residence time (MRT). In this context, CCS in soil and vegetation involves different processes than those involved in CO_2 injection into stable geological strata. The latter comprises of C capture from point sources (e.g., chimney of a coal-fired power plant, ethanol production from corn grains) and injection into stable and impermeable geological strata, old coal seams, oil wells or saline aquifers. CCS in land-based sinks is a natural process, based on photosynthesis and secure storage of biomass -C (above and below ground), soil organic C (SOC), and soil inorganic C (SIC) with a long MRT (Lal[17], 2004; 2010; Lal, *et al.*[32], 2021). Indeed, C sequestration in global cropland production is considered a

viable option to reduce GHG emission while producing nutritious food for the growing human population (Lu *et al.*[33], 2018).

CARBON FOOTPRINT OF CROPS AND CROPPING SYSTEMS

Global arable land use, comprising of 1500 million hectare (M ha) has a strong impact on CFP of agriculture. Thus, improving cropping systems can reduce emission of GHGs from soil and farming operations. Total GHG emission from cropping systems involves all farm operations e.g., seedbed preparation, application of fertilizers (e.g., Table 5 for India) and pesticides, irrigation, harvesting, grain drying, *etc*. There are large hidden C costs of all inputs such as fertilizers, herbicides, pesticides) (Lal, 2004a). CFP also involves emission from decomposition of straw and roots, and those from mineralization of soil organic matter (SOM) (Lal[17], 2004a).

The CFP of agroecosystems is affected by increasing use of inputs such as fertilizers, pesticides, tillage and irrigation. Millar *et al.*[34] (2014) reported that in crop production,75% of total emissions are attributed to N fertilizer use (both organic and inorganic). Use of N fertilizer affects CFP from production, application and direct emission of N_2O from soil following application of fertilizers. Millar *et al.* (2014)[34] also argued that once N is accounted for, there are no differences among organic, integrated, or conventional farming practices. Therefore, optimizing the use efficiency of inputs and enhancing productivity can spare the land. Vittis *et al.*[35] (2021) reported that the LFP of agroecosystems can be reduced by closing the yield gap, optimizing fertilizer inputs, and allocating 16 major crops across the global cropland. Vittis and colleagues estimated that global cropland area can be reduced by 50% of its current extent (1500 M ha) and spared land returned back to nature. Among numerous ecological benefits, the spared cropland would provide space for terrestrial C sequestration in soil and vegetation.

It is a high priority to reduce humanity's LFP by optimizing the land use and returning some land back to nature (Lal[27], 2018). Sparing current forests from conversion is an effective strategy, but can only happen if adequate livelihood options are available to those involved in agricultural horizontal expansion. Furthermore, closing yield gaps may not always lead to closing efficiency gaps. For example, optimizing or minimizing CFP by managing rate of N fertilization in some crops may differ from economic mineralization.

AGRICULTURAL MANAGEMENT PRACTICES TO REDUCE CARBON FOOTPRINT

Adoption of site-specific and science-based and sustainable management practices are critical to reducing CFP of agriculture/FSs, and leading to adaptation and mitigation of climate change, reducing per capita land use, and attaining the operating space within the planetary boundaries (Rockström *et al.*[36], 2009). In addition to reducing emission from crop production, GHG emission from agroecosystems can be off- set by sequestration of C in soil as SOC and SIC. Some examples given below indicate the options of reducing CFP by using science-based management practices. Liu *et al.*[37] (2018) estimated the gross CFP of crop production in China from 2000 to 2015 at 133 Tg of CO_{2eq} per year. However, soil C sequestration was estimated at 25 Tg CO_{2eq} per year, and thus, the net CFP for crop production in China was 108 Tg of CO_{2eq} per year. Liu and colleagues also observed that the farm CFP in China decreased by 9% because the proportion of crop residue retention increased by 26.4% and the improved use efficiency of N fertilization which also decreased the rate of input of N fertilizer by 8.4 Kg N/(ha.yr).

In India, total amount and rate of fertilizer use increased drastically between 1950 and 2020 [Table 5].Thus, emission from agriculture sector have increased since 1950s, partly because of low use efficiency of fertilizers (such as N) and unbalanced use of fertilizers. Sah and Devakumar[38] (2018) reported that

emissions have increased 161% from 14.81 Tg Ceq /yr (0.12Mg C eq/(ha.yr) in 1960 to 38.71 Tg Ceq (0.28 Mg Ceq/(ha.yr)) in 2010.This increase is attributed to decrease in area of less C-intensive coarse cereals and 22% increase in rice cultivation. Among crops, emission was 23.71 Tg Ceq for rice compared with 2.98 Tg Ceq for red gram. Emission of N_2O and CH_4 were the major contributors.

Rather than sequestration, conversion of natural to agricultural ecosystems can lead to loss of soil C pool. For example, a study on the impact of land use conversion was conducted for the

U.S. Western Corn Belt by Lu *et al.*[33] (2018). In comparison with the baseline period of 1980-2005, Lu *et al.*[33] found that cropland expansion more than tripled in 2006-2016, and the resultant land use change led to soil C loss of 90.5 ± 14.7 Tg C. Thus, grain production in this region changed from C neutral to C loss of 2.3 Kg C/kg of grain produced. Conversion of C-rich soils from natural to agro-ecosystems can lead to a negative C budget and increase the CFP. On the contrary, adoption of bioeconomy can reduce emissions and also reduce CFP. For example, a study in EU by O'Brien *et al.*[39] (2015) evaluated CFP of EU-27 for the period of 2000 to 2011, and found that promotion of bioeconomy decreased the LFP by 1% annually reaching 0.29 ha/capita by 2011. O'Brien and colleagues suggested that bioeconomy could decrease per capita cropland at the rate of 2%per annum and achieve the safe operating space within planetary boundaries by 2030.

Cropping systems, based on cover cropping and use of legume-based rotations can also reduce CFP. Based on a study for determination of CFP of durum wheat (*Triticum tugidum*) in Saskatchewan, Canada, Gan *et al.*[40] (2011) observed that decomposition of crop straw accounted for 25% of total emissions; those from production, transportation, storage and delivery of (Gan *et al.*[40], 2011) fertilizers and pesticides to farm gates and their application 43%, and emission from other farming operations 32%. Gan and colleagues also observed that the durum wheat grown in rotation with an oilseed crop (*Brassica* spp.) had CFP of 0.33 kg CO_{2eq} /kg of grain that was 7% lower than the cereal-cereal durum system. The CFP of durum was lowered by 17% when it was grown in rotation with N-fixing pulse crop, and by 34% in pulse-pulse-durum system (0.27 kg CO_{2eq}/kg of grain). These studies raise questions on the accounting system boundaries used. For example, if straw decomposition is counted as a loss, it may be based on the assumption that aboveground productivity is counted as a "sequestration". Therefore, it may be appropriate to use IPCC national accounting standards. It is also essential to develop a rule for partitioning system-level emissions to component crops.

Importance of crop rotations and residue management to reducing CFP of cropping systems has been reported in several studies. These practices are also called climate smart agriculture (FAO, 2013)[41]. Brankatschk and Finkbeiner[42] (2017) reported that ignoring crop rotation would lead to underestimation of the annual GHG savings of EU-28 rapeseed biodiesel by 1.67 $TgCO_{2eq}$ .Thus, they argued that crop rotations and straw harvest must be considered for the product CFP of bread, milk and first and second generation of biofuels, and these recommendations are relevant to all regions of the world.

In addition to cereals, soybean is an important crop as a source of protein, and oil. Castanheira and Freire[43] (2013) observed large variation in CFP of soybean ranging from 0.1 to 17.8 kg CO_{2eq}/kg of soybean depending on original land use and soil/crop management. The highest GHG emissions were calculated for tropical moist region when rainforest is converted to soybean cultivation. Without considering the land use conversion, CFP varies from 0.3-0.6 Kg CO_{2eq}/kg of soybean. Furthermore, all mechanical tillage systems have more GHG emission than a no-till (NT) system, and N_2O emission is an important factor affecting CFP.

Horticultural crops (e.g., vegetables) have a different CFP than cereals and other crops because of differences in farm operations and in inputs. In rapidly urbanizing China, Hu *et al.*[44] (2019) estimated the CFP of urban agriculture in Beijing with the focus on vegetables. Based on production, transportation and distribution of 1 kg of fresh vegetables, Hu and colleagues estimated the CFP (CO_{2eq}/kg of fresh vegetables) at 0.318 for conventional and 0.624-0.652 for home delivery systems.

TILLAGE SYSTEMS AND CFP OF CROPPING SYSTEMS

Global adoption of conservation agriculture (CA) is gaining momentum [Table 6]. Land area under CA is estimated at about 180 M ha or about 12.5% of global crop land (Kassam *et al.*[45], 2019), and it is widely adopted in South America (e.g., Brazil, Argentina, Chile, Paraguay), and is also gaining popularity elsewhere. Among numerous merits of a system-based CA are soil and water conservation, reduction in use of energy for farm operations, and in saving of time in establishing a second crop with a short time between harvesting one crop and seeding the second crop such as in the case of rice-wheat system in the Indo-Gangetic Plains of South Asia. A system-based CA can enhance use efficiency of inputs, sustain agronomic productivity and lead to sequestration of SOC in the surface layers (Lal[22], 2015; Lal *et al.*[46], 2017). Above all, conversion of plow-based tillage to NT-based CA can lead to saving in energy needed to perform primary and secondary tillage operations [Table 7]. Thus, CFP of a cropping system can be drastically reduced by conversion of conventional tillage to CA and saving in fertilizers and pesticide use through adoption of integrated soil fertility management, integration of pest management, and integration of crops with trees and livestock (Lal[25], 2020).The latter involves complex systems such as agro-pastoral, silvo-pastoral, agri-silvo and agro-silvo-pastoral systems (Okigbo & Lal[47], 1977; Nair *et al.*[48], 2009; Rosenstock *et al.*[49], 2019).

With tillage and inputs being important determinant of CFP of cropping systems, use of precision agriculture technology (PATs) can also impact the magnitude of CFP by savings of inputs (Brown *et al.*[50], 2016). Adoption of PATs in conjunction with CA and drip sub-fertigation can reduce CFP.

PLANTATION AND HORTICULTURAL CROPS

Similarly to cropland, coffee and horticultural crops also have a large CFP. Ratchawat *et al.*[51] (2020) reported CFP (kg CO_{2eq}/kg) of Robusta coffee products at 0.40 ± 0.12 of coffee cherry, 0.55 ± 0.08 for roasted coffee and 0.56 ± 0.08 for ground coffee. Ratchawat and colleagues estimated that almost 70% of all GHG emission came from chemical fertilizers involving both production and application. WFP (m^3/kg) was 10 for coffee cherries and 27 for roasted and ground coffee. Based on the data from 116 coffee farms in five Latin American countries, van Rikxoort *et al.*[52] (2014) evaluated CFP of four production systems: (1) traditional polyculture; (2) commercial polyculture; (3) shaded monoculture; and (4) unshaded monoculture. Rikxoort and colleagues found that polycultures have a lower mean CFP of 6.2-7.3 Kg CO_{2eq}/kg of parchment coffee than monocultures of 9.0-10.8.kg.It was also found that traditional polycultures have a much higher C stock in the vegetation at 42.5 Mg/ha than the unshaded monoculture of 10.5Mg/ha. Martins *et al.*[53] (2018) computed the CFP of Brazilian coffee production from 2004-2005 to 2014-2015. Based on data of plantation area and coffee production, Martins and colleagues estimated that CFP and WFP were 19.79 Tg CO_{2eq} and 49284 M m^3 of water, respectively. Martins and colleagues computed CFP for total resource use and impacts, which differs than the way it is defined in this article as footprint per unit of product or human activity.

LIVESTOCK MANAGEMENT

Livestock are an important component of agriculture, especially in case of small land holders and resource-poor farmers. In comparison with crops, livestock management is resource-intensive and requires high energy, water, land, nutrient and infra-structure investment. Therefore, it is important to identify practices

Table 6. Global adoptions of conservation agriculture (adapted from Kassam *et al.*[45], 2019)

Region	Global Cropland Area Under CA (10^6 ha)
South America	69.90
North America	63.18
Australia and NZ	22.67
Asia	13.93
Russia + Ukraine	5.70
Europe	3.56
Africa	1.51
Total	180.44

Practiced on 12.5 % of global cropland area.

Table 7. Carbon emission from diesel consumption for different tillage operations, fertilizers and pesticide use (adapted from Lal[17], 2004)

	Farm operations	Carbon footprint	Units
I	Tillage Sub-soiling	11.3 ± 2.8	Kg Ceq/ha
	Moldbourd Plowing	15.2 ± 4.1	
	Chisel Tillage	7.9 ± 2.3	
	Heavy Disc Plowing	8.3 ± 2.5	
	Chisel Tillage	4.0 ± 1.9	
	Heavy Disc Plowing	8.3 ± 2.5	
	Field Cultivation	4.0 ± 1.9	
	Rotary hoeing	2.0 ± 0.9	
II	Fertilizer Nitrogen	1.3 ± 0.3	Kg Ceq/ Kg nutrient
	Phosphorus	0.2 ± 0.06	
	Potassium	0.15 ± 0.06	
	Lime	0.16 ± 0.11	
III	Pesticides Herbicides	6.3 ± 2.7	Kg Ceq/ Kg a.i.
	Insecticides	5.1 ± 3.0	
	Fungicides	3.9 ± 2.2	

of sustainable management of livestock, and is also critical to educate the consumer about judicious use of animal-based products (i.e., meat, dairy). Globally, livestock sector is estimated to account for 15% of GHG emission, 80% of these emissions originate from ruminant animal systems involving enteric fermentation and manure management (Persson *et al.*[54], 2015). Thus, emissions from livestock sector have raised numerous questions regarding the possibility of reducing animal-based diet as a strategy to reduce emission of GHGs.

Livestock is an important component of India's agriculture sector. In 2012, India's livestock sector produced 304,31 and 4 Tg in CO_{2eq} of enteric CH_4, manure CH_4,and N_2O, respectively (Patra[55], 2017). The relative contribution (% of total) of different species to GHGs was 55, 37, 4, 2.1 and 1 for cattle, buffalo, sheep, goat, pig and other animals, respectively. Enteric fermentation was the major contributor and accounted for 89.7% of the total emissions from India's livestock sector followed by manure CH_4 (9.2%) and N_2O (1.2%). The CFP (Kg CO_{2eq}/kg of the produce) was estimated at 1.21 for cross-bred cattle to 2.96 for indigenous cattle. In Southern Australia, Ridoutt *et al.*[56] (2014) estimated the land area footprint of beef cattle. The land area needed (m^2/kg of live weight) ranged from 86 to 172. Ridoutt and colleagues observed that these results were approximately 10 and 1000 times the normalized carbon and water scarcity footprint data, and

highlight the importance of taking into account the land quality in the calculation of LFP.

In Mato Grosso, Brazil, Cerri *et al.*[57] (2016) assessed CFP of cattle farming for beef production. Evaluating 22 farms with cumulative pastureland area of 60,000 ha, Cerri and colleagues observed that the largest source (89%-98%) of GHG in extensive beef production is contributed by animals. Of these, 67-79% come from enteric fermentation followed by those from manure (20%-33%).Other sources of emission were agricultural inputs and energy. The CFP of a farm with herd size of 2000 cattle was 4.8-8.2 kg CO_{2eq} per kg of the liveweight gain. For farms raised animals, CFP ranged from 5.0 to 72 kg of CO_{2eq} per kg of the live weight gain. Therefore, herd size and management to reduce enteric fermentation are critical to reducing CFP of beef cattle. Rojas-Downing *et al.*[58] (2018) studied a representative farm based on grazing dairy practices in the state of Michigan, USA, and proposed a food footprint (FFP). Using FFP, Rojas-Downing and colleagues identified a most sustainable milk production level (8618 kg of milk per cow per year) which was 19.4% more than the average milk production (7215 kg per cow per year).

Furthermore, most sustainable pasture composition for the state of Michigan was found to be 90% for tall fescue with 10% for white clover. Thus, there is a strong need for identification of site-specific management and production standards. Yan *et al.*[59] (2013) evaluated GHG emissions from pasture-based milk production using fertilizer N or white clover at a research farm in Ireland between 2001 and 2006.The white clover based system had 11 to 23% lower CFP than fertilizer N system (0.86-0.87 *vs.* 0.97-1.13 kg CO_{2eq}/kg of energy-corrected milk). Furthermore, emissions of both N_2O and CO_2 were lower in white clover system but those of CH_4 were similar in both systems.

Because of its large foot print (LFP, WFP, CFP, FFP *etc.*), there is a strong need for development of a climate-neutral livestock production system .Thus, Ridoutt[60] (2021) proposed a radiative-forcing (RF) based livestock production system. Based on Australian sheep production for meat. Rideout reported that RF plateaued at 0.64 mV/m^2, and is projected to decrease with better management. The new RF-based assessment of livestock may be adopted by the ISO for aligning food system with the Paris Accord.

OPTIMIZING HUMAN DIET FOR ADDRESSING CFP OF AGRICULTURE

The food system, being a major contributor to anthropogenic emissions (Röös *et al.*[15], 2014), must be critically assessed with regards to the source of GHGs [Figure 2]. Primary GHG involved in FSs are CO_2 from deforestation, land use conversion, plowing, and erosional processes [Figure 2]. Erosion-induced transport of SOC can be a major source of all three gases (Lal[12], 2004; Lal *et al.*[61], 2021a; Lal *et al.*[32], 2021). N_2O is primarily contributed by soil through use of inorganic and organic fertilizers. CH_4 is contributed from livestock and rice paddies and wetlands [Figure 2]. The U.N. FSS of 2021 identified some specific strategies to advance SDGs or the Agenda 2030 of the United Nations (Lal *et al.*[12], 2021). The environmental footprint of the diet of 7.8 billion people, projected to be 9.7 B by 2050 and 11 B by 2100 (U.N., 2019)[6], is an important factor to sustainable management of soil and water resources but also to addressing the issues of global warming along with quality and renewability of water resources. Leach *et al.*[30] (2016) reported that the EFP of food production spans multiple dimensions including CFP based on GHG emission, nitrogen footprint (NFP) and water use (both green and blue, WFP), and land use (LFP). It is, thus, important to identify diet that can minimize each of these FP values, especially those diets which have synergies rather than tradeoffs among different low FP diets.

Beef production has received a considerable attention because of its high EFP (e.g., CFP, NFP, WFP, LFP). Buratti *et al.*[62] (2017) reported that organic systems (Kg CO_{2eq}/kg of live weight) is 24.62 compared with 18.21 for the conventional systems because enteric fermentation is the primary factor in GHG emission with

a range of the global CF value. Ibidhi and Ben Salem[63] (2020) computed WFP of a wide range of livestock, and reported that WFP of meat is higher than that of either milk or eggs. Ibidih and Salem reported that WFP of beef is much larger than WFPs from sheep, goat, pork and chicken. These differences in WFP are attributed to differences in the food conversion ratio among animals. Most ruminants (e.g., cattle, sheep and goat) have a poor food conversion ratio than those of the monogastric animals (e.g., poultry and swine).

Similar to beef production, milk production has also attracted a lot of attention. Velarde-Guillen *et al.*[64] (2022) reviewed CFP of milk production in Latin America. The range of CFP observed in the Latin American region was 1.54 to 3.57 kg CO_{2eq} /kg of fat and protein corrected milk. Velarde-Guillen *et al.*[64] (2022) observed that, in Latin America, cattle system and region have a more significant impact on milk CFP than the feeding management (e.g., zero-grazing, semi-confinement, and pasture).

Espinoza-Orias*et al.*[65] (2011) estimated the CFP of one loaf of slice bread (800 g) consumed at home on the basis of several parameters such as country of origin of wheat, type of flour, and type of packaging. The lowest CFP was observed for the whole wheat thick sliced bread wrapped in a plastic bag, and the highest for the wheat bread packed in a paper bag. Further, CFP could be reduced by 25% by avoiding toasting and refrigerated storage of bread.

Conventional *vs.* organic farming is another important factor affecting CFP of bread. Treu *et al.*[66] (2017) computed the CFP of conventional *vs.* organically grown food products. Treu and colleagues observed that CFP of the conventional *vs.* organic diets are essentially similar at ~1250 kg CO_{2eq} per capita per year. However, the land area use to provide food is 40% greater for organic *vs.* conventional diet at 1900 and 2750 m^2 of land per capita per year, respectively. Furthermore, the average conventional diet contains 45% more meat and organic diet 40% more vegetables, fruits and legumes (combined). Treu and colleagues also observed that animal-based food products dominate the CFP in both diets and land use and accounts for 70 to 75% of CFP in both diets. Treu *et al.*[66] concluded that diet-related CFP can be reduced by shifting towards diets with less animal-based food products, and there is not much difference in CFP among organic *vs.* conventional system of food production.

FOOD WASTE AND CFP OF AGRICULTURE

Agriculture is a resource-intensive enterprise and a lot of resources are consumed in agroecosystems (e.g., soil, water, energy, chemicals). Avoidable food waste incurs loss of resources with adverse impacts on environment. World wastes 1.4 Gt of food every year. Globally, as much as 931 Mt of food is wasted from retail, food service and household, and it is enough to feed 820 M food-insecure people (Pearson[67], 2021). The U.N. SDG #12.3 is aimed at reducing the food waste by 50% by 2030. (U.N., 2015)[11]. Food waste varies among nations, and the U.S discards food more than any other country (40 Mt). This is 30 to 40 % of the entire food supply and is equivalent to 99.3 kg/per person per year (RTS, 2020)[68]. Food waste in the U.S. comprises 22% of all municipal solid waste. Yet, a large number of population is also food-insecure. As many as 35 M people in the U.S. were food insecure prior to COVID 19, and the number of persons vulnerable to food insecurity has increased to 50 M in 2022 (RTS, 2022)[69]. In the U.S., Economic Research Service estimated that for the baseline year of 2010 the food loss was 31% of food supply, equaling 133 billion pounds (523 billion kg) at an estimated value of $161.6 billion. The 2030 SDGs aim to cut food loss at the retail and consumer level by half to 66 billion pound (261 billion kg), (EPA, 2016)[70]. Reutter *et al.*[71] (2017) estimated that Australian food waste represents 9% of total water use and 6% of GHG emissions.

Based on a case study on U.K., Tonini *et al.*[72] (2018) estimated the global warming impact of the avoidable food waste at 2000 to 3600 kg CO_{2eq} per Mg of food waste. Schott and Cánovas[73] (2015) estimated from a

study in Sweden that an average of 35% of household food waste can be avoided, which will reduce GHG emission of 800-1400 kg of CO_{2eq} per Mg of food. Wasted food represents a high magnitude of energy, nutrient and virtual water rich stream with adverse effects on environment and resource use. In China, Song *et al.*[74] (2018) estimated average food waste at 12-33 kg per capita per year. With a CFP of 30-96 kg CO_{2eq} per capita per year. Song and colleagues also observed that animal-based food accounts for 5%-18% in weight but 18%-40% in CFP because of the extra resources involved in animal-based food. A thorough understanding of economic and ecological costs involved of the food wasted is essential.

Therefore, reducing food waste, estimated at ~30% of food produced globally, can drastically decrease the CFP of agroecosystems. Globally, food waste contributes 11% (3.3 Gt of CO_{2eq}) of all GHG emissions: 43% at home, 40% at restaurants,16% at farms and 2% at manufacturers (RTS 2022)[69]. If food waste is a country, it is the 3rd largest emitter of GHGs after China and U.S. The resource impact of food waste can drastically influence the CFP and must be accounted for especially in limited resources such as energy, water and prime agricultural land. In India, Kashyap & Agarwal[75] (2020) estimated total food loss in harvest and post-harvest stages for the food supply chain for some selected food items. They reported that food losses amounted to 58.3 ± 2.22 M Mg in 2013 with the highest losses in sugarcane and rice with a large loss of water resources. LFP and CFP associated with food loss were estimated at 9.58 ± 0.4 M ha and 64.1 ± 3.8 Tg CO_{2eq}, respectively, with rice contributing substantially to both. In 2010, U.S. EPA estimated that food waste accounted for nearly 14% of total solid wastes (Golan[76], 2013). Nonetheless, a significant gap exists in the understanding of the food waste implications of the rapidly developing economies (Parfitt *et al.*[77], 2010).

The food-energy-water-soil or the FEWS nexus (Lal *et al.*[46], 2017) is an important concept to assess the impact of food waste on CFP. Kibler *et al.*[78] (2018) characterized food waste on the FEW when food produced is not consumed by human or animals. Kibler and colleagues observed that different food waste management options (e.g., landfilling, composting, anaerobic digestion, incineration, waste prevention) provide diverse pathways to manage CFP. These researchers proposed a "food-waste-system" approach to optimize resources and reduce the CFP.A similar approach was adopted by Sarker *et al.*[79] (2016) who proposed a conceptual methodology for characterizing inter-connected FEW components.

Because of large differences in RFP of foods, there are several options for the general public to modify lifestyle and make it more sustainable. Schanes *et al.*[80] (2016) proposed a novel framework for consumers to lower their CFP with the focus on food consumption.

SAVING LAND AND NATURAL RESOURCES BY AVOIDING FOOD WASTE

Global food waste aggravates global warming, and depletes the finite natural resource base while also polluting the environment. It is equivalent to 2.2 Gt of CO_{2eq} of CFP in terms of GHG emissions. The per capita food wastage CFP (Kg CO_{2eq}/per person per year) is estimated by (FAO, 2014)[81] at 860 for North America and Oceania, 810 for industrialized Asia, 680 for Europe, 540 for Latin America, 350 for North Africa and West Asia, 350 for South and South East Asia, and 210 for Sub-Saharan Africa (FAO,2014)[81]. The equivlent WFP is shown in Table 2, and the world average WFP for food waste is 38 m^3/capita per year (FAO, 2013)[41].The food waste represents 4.4 M Km^2 of land area on which food is produced and lost each year. This land area is larger than that of the Indian Sub-Continent (Pearson[67], 2021). Therefore, humanity must create a future where both nature and people thrive, flourish and live in harmony with one another.

CONCLUSION

Humanity's unsustainable footprint is likely to increase with growing and progressively affluent world population. Humanity's impact on planetary processes, referred to environmental or ecological footprint,

comprises of a range of sub-components (i.e., land, water, energy, fertilizers, nitrogen, biodiversity).

EFP, and more specifically CFP, can vary widely because of using different reference systems of the studies and differences in system boundaries. Therefore, standardization of the methodologies following the ISO is critical to obtaining credible information for making sound decisions.

Humanity's CFP can be reduced by making appropriate choices in food systems including production and supply chains, changing lifestyle and dietary preferences, and using agricultural systems which narrow the yield gap and can produce more from less.

The global warming impact of the avoidable food waste at 2000 to 3600 kg CO_{2eq} per Mg of food waste. Globally, as much as 931 Mt of food is wasted from retail, food service and house hold, and it is enough to feed 820 M food-insecure people. Food waste, a heinous crime against nature, is not acceptable.

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The author contributed solely to the article.

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Carbon Footprints

Perspective

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Carbon footprints, informed consumer decisions and shifts towards responsible agriculture, forestry, and other land uses?

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Abstract

The urgent global reduction of greenhouse gas emissions depends on political commitments to common but differentiated responsibility. Carbon footprints as a metric of attributable emissions reflect individually determined contributions within, and aggregated national contributions between, countries. Footprints per unit product (e.g., of food, feed, fuel, or fiber) require a lifecycle analysis and support individual decisions on consumption and lifestyles. This perspective presents a framework for analysis that connects the various operationalizations and their use in informing consumer and policy decisions. Footprints show geographical variation and are changing as part of political-economic and social-ecological systems. Articulation of footprints may trigger further change. Carbon footprints partially correlate with water and biodiversity footprints as related ecological footprint concepts. The multifunctionality of land use, as a solution pathway, can be reflected in aggregated footprint metrics. Credible footprint metrics can contribute to change but only if political commitments and social-cultural values and responsibilities align.

Keywords: Agriculture, forestry and other land uses (AFOLU), ecological footprint, indirect carbon emissions, land use, lifecycle analysis, nationally determined contributions (NDC), theories of change, theories of place

INTRODUCTION

Historically, the concept of carbon footprint emerged as part of a more comprehensive "ecological footprint" concept[1-3], which is the area "of productive land and water ecosystems required to produce the resources that a population consumes and to assimilate the wastes that the population produces, wherever on Earth that land and water may be located" as its primary metric [Figure 1]. The choice of "area" as a metric, linked to the footprint metaphor, helped to popularize the concept, while it could be converted to a temporal equivalent in calculating the annual "overshoot day", where consumption starts to exceed sustainable supply[4].

Fifty years after Meadows *et al.*[5] (1972), the urgency of climate action has been widely accepted, but the pathways to deal with it remain contested. Nation-states, a globalized corporate sector, and global citizens are important parts of the problem and have to be part of the solution. The latest synthesis by the Intergovernmental Panel on Climate Change (IPCC) of the human influence on C cycles shows[6] that the increased concentration of greenhouse gasses (GHG) has already reached a global warming effect of 1.5 °C. However, emission of "cooling gasses" such as sulfur dioxide is neutralizing part of the warming, defining an inconvenient truth on a tradeoff between air pollution control for local health benefits and global climate change control. Total anthropogenic GHG emissions can be attributed to the country where they occurred, the economic activity and sectors that caused them, the products generated, or the consumers whose needs were satisfied. However, the likelihood of gaps between different accounting approaches (and/or for double-counting) is considerable when attributions to countries, sectors, products and citizens are intermingled. However, that is the current reality with multiple footprint concepts.

As nation-states have collectively failed in the first thirty years after the UN Framework Convention for Combatting Climate Change (UNFCCC) to resolve the necessary energy transition and address the drivers of deforestation and degradation in a timely fashion, citizens' concern over the urgency of the issues kept increasing. Pathways towards solutions have a territorial dimension [mostly based on nation-states and their nationally determined contributions (NDC)[7]] and a supply/demand, market-based one that depends on actors along supply and value chains as well as consumers and voluntary, individually determined contributions to emission control. Both the territorial and market-based pathways are needed to decouple economic success, resource use, and GHG emissions[8] and jointly achieve the Sustainable Development Goals (SDG).

An alternative arena for state-based action arose in the personal responsibility for the "footprint" consequences of consumption and lifestyle choices. Such initiatives started especially in the Global North, driven by young people, but were followed up elsewhere[9,10]. The (threats of) boycotts of products, such as palm oil, which were singled out in public communication, led to responses by part of the global corporate sector, keen to protect their branding and public image. The result has been an avalanche of declarations, commitments, and stated ambition to become deforestation-free, carbon-neutral, carbon-negative, *etc.*[11]. Nation-states, a globalized corporate sector, and global citizens interact in the "governance" and "consumption-based" interfaces [Table 1] that shape current actions.

Table 1. Three ways global anthropogenic emissions can be accounted for and governed

	Nation-states	Private (corporate) sector	Consumers, citizens
Accounting target	Net anthropogenic emissions within national boundaries; pledged and supported NDC	Emission intensity (attributable emissions per unit economic turnover)	Per capita emissions; Individual footprints (domestic + global)
Gaps	Accountability for EET, including imported biofuels; international waters; C sink saturation	Transnational corporations; sea and air transport; responsibility for "indirect land-use change" (ILUC)	Lifecycle accounting beyond consumable products, including "services", waste, and recycling
Interfaces	Governance: carbon markets created by tradeable emission rights for corporations; REDD+; carbon tax at international borders		Response to changing prices for goods and services
	Fear of loss of sovereignty, national standards to regain trust and maintain exports	Consumption-based: Consumer pressure to obtain "cheap but green" products; sector-level standards, commitments, certification	

NDC: Nationally determined contribution; EET: emissions embodied in trade: REDD+: Reducing Emissions from Deforestation and (Forest) Degradation.

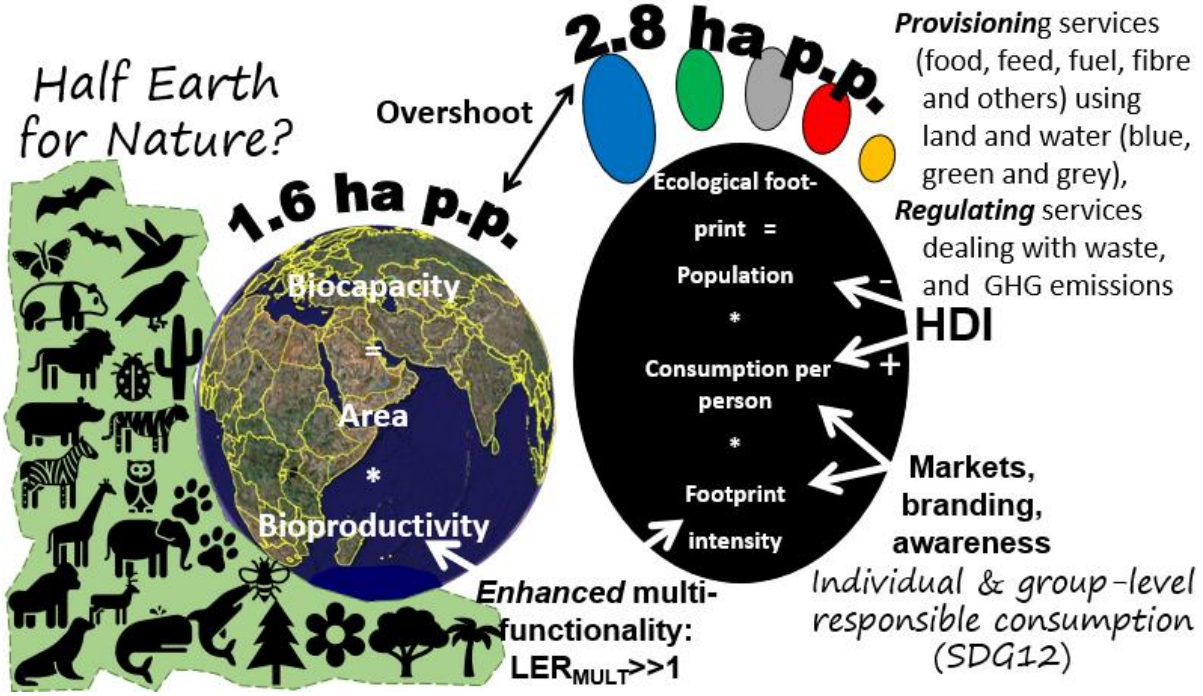

Figure 1. Visualizing the "footprint exceeding the planet" metaphor with global data for 2017. Available from: https://data.footprintnetwork.org/#/countryTrends?cn=5001&type=earth [Last accessed on 15 Apr 2022], and the leverage points of the Human Development Index (HDI), individual and group-level responsible consumption, and increased bioproductivity (evaluated at multifunctional level). The half-earth for nature debate[42] is not yet reflected in footprint calculations.

Where nation-states became the primary agents in UN-based discussions, the route to change via global citizens, consumer power, and a responsive corporate sector (that wants to be seen as responsible for their individually determined contributions) remains a separate track with challenging "market-based" interfaces with NDCs of the countries in which goods are produced, consumers reside, and/or companies have their legal basis.

Carbon footprints relate GHG emissions to decisions made. Wiedmann and Minx (2008)[12] provided an often-cited definition of "carbon footprint" in a context of ecological economics as "The carbon footprint is a measure of the exclusive total amount of carbon dioxide emissions that are directly and indirectly caused

by an ***activity*** or is accumulated over the life stages of a ***product***. This includes activities of individuals, populations, governments, companies, organizations, processes, industry sectors, etc. Products include goods and services. In any case, all direct (on-site, internal) and indirect emissions (off-site, external, embodied, upstream, downstream) need to be taken into account." Subsequently, the carbon-equivalence of other GHGs has been included, as indicated in the instruction to authors of this journal: "The term carbon footprint refers to the emissions of all greenhouse gases including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and chlorofluorocarbons, and is expressed as the amount (tons) of CO_2 produced during a given period."[13].

The quantification of these various footsteps can be derived from a common basis of accounting for land use [Figure 2]. It all starts from a land cover classification that allows all land units to be mapped without double-counting or gaps so that area fraction, time-averaged (system level) C stocks, and the emissions of N_2O and CH_4 can be measured. This is the basis of national GHG accounting of the land-use sectors, with input production and transport accounted elsewhere. However, land use yields marketable commodities, and these can be the basis of product-based accounting when other parts of their lifecycle are added and summed for the footprint of food production as part of the global food system. When consumption is differentiated by societal groups or individuals, further footprint calculations become possible.

Four carbon footprint concepts play a role in discussions on both supply and demand-based pathways [Figure 2]: (1) historical and current per capita emissions as an argument of fairness in NDCs declarations; (2) emissions per unit economic activity as the economic footprint for the efficiency argument in NDC declarations; (3) product-level footprints derived from a lifecycle analysis (e.g., for food, feed, fuel, or fiber); and (4) consumption-level, individual footprints, differentiated by wealth and lifestyle. The latter types of carbon footprints supposedly inform consumer decisions and support shifts towards development strategies with low emissions of carbon and other greenhouse gasses. Footprints can function as boundary objects as they are entities that enhance the capacity of an idea, theory, or practice to translate across culturally defined boundaries, for example, between communities of knowledge or practice[14]. Their derivation and use are a form of boundary work[15] and have to meet the quality criteria of credibility, salience, and legitimacy.

In reviewing evidence for such a theory of change, we focus on three questions:

Q1. How are the operational definitions of various types of carbon footprints related to consistent accounting for GHG emissions?

Q2. How are footprint concepts used as boundary objects in public and private decision-making?

Q3. How might footprint concepts be improved?

For Q1, we provide backgrounds on human impacts on the global C cycle, discuss ecological footprints as an umbrella concept, and contrast footprint concepts 1-4 as part of governance- and business-based climate solutions. For Q2, we introduce four levels of leverage on complex, adaptive social-ecological systems, discuss theories of place and change across scales, and review theories of (induced) change concerning carbon footprints. For Q3, we summarize the findings on the first two questions and discuss ways forward.

Human impacts on the global C cycle

The chain of land users/producers, processors/transporters, and consumers has become increasingly global in its operational dynamics, with fossil-based energy sources interacting with and potentially substituted by

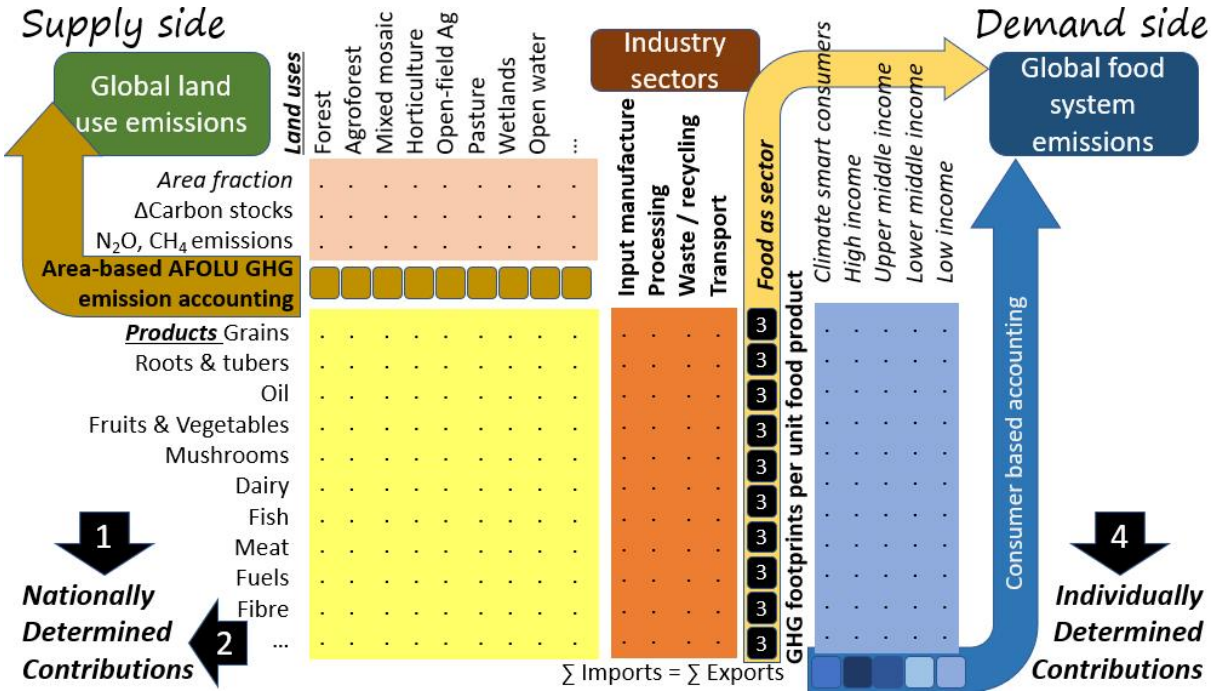

Figure 2. Nationally and individually determined contributions to global emission reduction based on the relationship between AFOLU land use (agriculture, forestry, and other land uses), the production of tradable commodities that through lifecycle analysis leads to product level footprints, and potentially informed consumer decisions. Four uses of footprint metrics are discussed in the text (modified from Ref.[27]).

land-based emissions [Figure 3]. Fossil fuels and land-based emissions have an increasing impact on atmospheric GHG concentrations as terrestrial and oceanic sinks are becoming saturated and risk becoming net emitters in a changing climate[16,17].

The global carbon budget can be described as having five major components, each with uncertainties but with internally consistent estimates[18]: (1) fossil CO_2 emissions (E_{FOS} 9.4 ± 0.5 GtC year^{-1}; based on energy statistics and cement production data); (2) emissions from land use and land-use change (E_{LUC} 1.6 ± 0.7 GtC year^{-1}; mainly deforestation, based on land use and land-use change data and bookkeeping models); (3) atmospheric CO_2 concentrations and its growth rate (G_{ATM} 5.1 ± 0.02 GtC year^{-1}, measured directly and computed from the annual changes in concentration); (4) the ocean CO_2 sink (S_{OCEAN} 2.5 ± 0.6 GtC year^{-1}); and (5) the terrestrial CO_2 sink (S_{LAND} 3.4 ± 0.9 GtC year^{-1}; estimated with global process models constrained by observations). The sum of the first two approximately equals that of the latter three ($E_{FOS} + E_{LUC} = G_{ATM} + S_{OCEAN} + S_{LAND}$). Footprints refer to the first two ($E_{FOS} + E_{LUC}$), taking the latter two ($S_{OCEAN} + S_{LAND}$) for granted, but both sinks are at risk. Technically, the rules for national reporting of GHG emissions have separate sections for croplands, grasslands, forestry, and wetlands, but all are based on accounting for changes in C stocks and recurrent emissions of CH_4 and N_2O and are mutually consistent[19]. However, the accounting is land-based and does not include industrial production of inputs such as fertilizer, or subsequent transport and processing (that are handled in separate chapters of the IPCC national accounting rules).

Annex I countries (also known as the Global North) could thus far meet their international obligations by outsourcing emission-intensive heavy industry to non-Annex I countries[20] and protecting their domestic forests while increasing their external footprint for agricultural and forestry products. Meyfroidt *et al.*[21] (2010) estimated a 50% area substitution from global trade statistics. Area footprints are translated to carbon

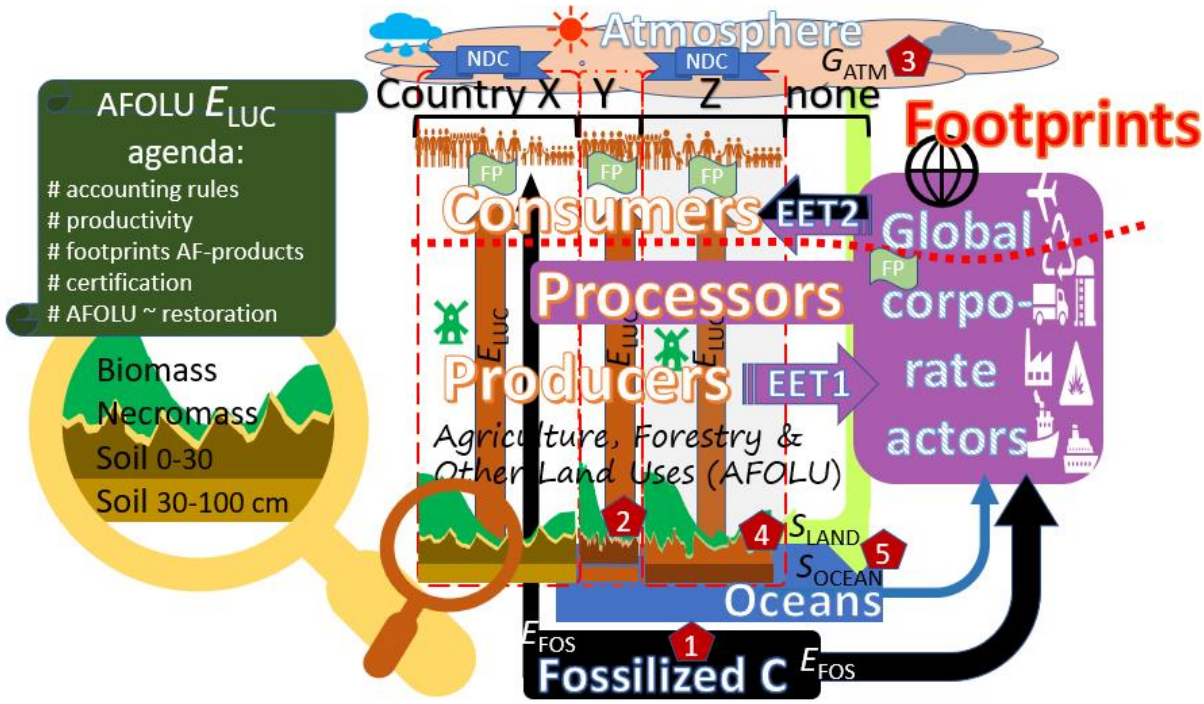

Figure 3. Overview of the cross-scale relations between local C stocks and GHG emissions and global climate change, with a nation-state-based relationship between land use and consumers and one in which global trade and global corporate actors play major roles. Global carbon budgets consider emissions from fossil sources (E_{FOS}) and land use (E_{LUC}), increases in atmospheric concentration (G_{ATM}), and the sink strength of oceans (S_{OCEAN}) and terrestrial systems (S_{LAND}). GHG: Greenhouse gasses.

footprint in the emissions embodied in trade (EET) literature[22-24], but may have further consequences in terms of biodiversity, water, pollution, or social impacts[25,26]. Country-level responsibility for and crediting of terrestrial (let alone oceanic) sinks remain an unresolved issue in the UNFCCC arena and are not addressed in current footprint definitions[27,28]. The sum of current NDC declarations still falls short of the globally accepted UNFCCC goals, even if there would not be an NDC implementation gap.

Footprints as part of governance- and business-based climate solutions

The corporate sector tries to build trust in its "brands" through its public commitments to social and environmental impacts. Without standardized reporting requirements that are compatible with national GHG accounting, however, the necessary public pressure to follow through on commitments is hampered. While well-intentioned global citizens try to minimize their "footprints", without clarity on how this contributes to NDCs, there is a risk of multiple claims of credits and a lack of synergy between governance- and business-based climate solutions. Behavioral change in response to consumption options can contribute to climate change mitigation[29], as the action may have to start at home[30], or in choices of how to travel away from and back to home. One of the accountability gaps is in the aviation industry. The global scale, distribution, and growth of aviation have implications for climate change[31]; these have been kept outside the reach of national accounting and policy responses so far but are on the radar screen of those wanting to express personal responsibility. The degree to which climate policies can effectively target household consumption and behavioral decisions is probably key to low-carbon futures. Footprints can help in the process as a relevant metric, with adequate attention to standards, data quality, and consistency. Standardization of footprint calculations for businesses and products has been achieved (ISO 2018a, b, ISO 2019), with specific challenges for the footprint of recycled products[32].

Current experience with demand-side solutions for climate mitigation is that the bottom-up drivers of household energy behavior change in ways that depend on the national context[33]. The distribution of household carbon footprints is largely unequal within and across countries in Europe[34]. Inequality is even larger globally as carbon footprints relate to socially desirable outcomes such as income, equality, education, nutrition, sanitation, employment, and adequate living conditions - the totality of the SDG agenda 2030[35-37]. Pathways between metrics such as carbon footprints and SDG attainment will need to be better understood.

Ecological footprints as an umbrella concept

Despite its "rhetorical appeal", scientific critiques and methodological weaknesses were seen as the demise of the ecological footprint as a basis for public policy processes[3]. This history may be repeating itself in the next reincarnation of multidimensional "environmental space" as the planetary boundary concept of Rockström *et al.*[38] (2009) and its safe operating space for humanity[39].

The overshoot of the human footprint over the global biocapacity [Figure 1] suggests three types of leverage points to reconcile supply and demand[36]:

A. More efficient (less resource-dependent) ways to achieve well-being for a growing population (along with progress to self-regulate human population size by supporting gender-balanced education;

B. Enhanced multifunctionality of land use (technically, the land equivalent ratio for multifunctionality (LER_{MULT}) is substantially above 1[36,40]).

C. Responsible consumption by well-informed and aware consumers, reliable footprint information, along with a continued increase in Human Development Index[41].

The footprint metaphor of current human impacts exceeding the carrying (or bio-)capacity of the planet [Figure 3] does not yet include impacts on biodiversity, for which a claim of "Half Earth for Nature"[42,43] is currently negotiated as part of the post-2020 Convention on Biodiversity targets (possibly watered down to a 30% target, and strongly dependent on how nature is interpreted[44]).

As many land uses are "multifunctional" and contribute to multiple commodity flows, an attribution system is needed within each type of footprint considered, e.g., based on the LER_{MULT} metrics[36]. Land-use change is a multi-phased process. The sharing across commodity flows of responsibility for emissions (stock change) is not easy, as a typical sequence of logging for high-value timber, overlogging for pulp-and-paper industry, and conversion to oil palm (*Elaeis guineensis*), coffee (*Coffea arabica* and *C. canephora*), or cocoa (*Theobroma cacao*) production shows. An example with apparently "deforestation-free" conversion of swiddens that otherwise would have recovered as secondary forests to coffee gardens was described for Vietnam[45,46].

Sustainable intensification of agriculture has been recognized as one of the requirements for human prosperity and global sustainability[47], but how this relates to simultaneously closing existing yield and efficiency gaps in multifunctional land use and their GHG emissions per unit product remains contested. In minimizing the ecological footprint of food, both the environmental impacts and the volume of production over which the load is shared are relevant[48]. The environmental impacts depend on "efficiency gaps" (where more inputs are needed and hence GHG emissions are higher than strictly necessary) and "yield gaps" (where achieved yield levels are lower than potential). Quantitative analysis for specific commodities

suggests that, indeed, an intermediate level of "intensification" can minimize footprints[49]: a comparison of closing yield gaps in oil palm by increased fertilizer use, with associated increased emissions of N_2O as a potent GHG, suggested that minimizing the carbon footprint by optimal fertilizer use depends on past land cover history[50]. The results demonstrate the relevance of variation of carbon footprints within a commodity such as palm oil can easily exceed differences between average footprints of different bioenergy crops. This variation was discussed as "management swing potential" by Davis *et al.*[51] (2013). The size of the management swing potential is an argument for differentiating footprints of alternate production streams rather than of products as such.

Among the various components of the ecological footprints, the water footprint[52] may well be most compelling as the combination of increased demand for reliable, clean water coincides with more variable climates in which both drought and floods are a risk, and a diminished capacity of landscapes to buffer water flows[53]. Water footprints normally include the use of "blue" water (surface or groundwater), direct use of rainfall buffered in soils "green" water, and a "grey" water component (how much clean water is needed to dilute pollution to acceptable standards). A recent proposal for alternative metrics suggests using the water use by natural vegetation as the point of reference, as both downwind rainfall and downstream river flow are likely adjusted to that level of water use, and both increased and decreased groundwater flows can induce problems[54].

The carbon footprint metaphor appeared at the turn of the millennium and spread quickly, initially as a carbon component of the ecological footprint[28,55]. The initial estimates of an area equivalence were abandoned for the current definition in emission units. The basic appeal was that the carbon footprint of nations could add a global, trade-linked analysis to existing national emission accounting[56]. An overview of carbon footprint analysis by Wang *et al.*[57] (2010) stated: "This report explores the apparent discrepancy between public and academic use of the term 'carbon footprint' and suggests a scientific definition based on commonly accepted accounting principles and modeling approaches. It addresses methodological questions such as system boundaries, completeness, comprehensiveness, units, and robustness of the indicator" and "Whatever method is used to calculate carbon footprints, it is important to avoid double-counting along supply chains or life cycles".

Four levels of leverage on complex, adaptive social-ecological systems

Interventions in complex adaptive systems, such as landscapes in which various social actors make a living interacting with global markets while influencing local soils, watershed-level streamflow, and global atmosphere and climate, can easily have unexpected results. As there are many aspects to consider across many contexts, the classification Meadows (1999)[58] developed based on her experience with global system models of ways to leverage complex adaptive systems can be used. Simplified, the classification groups parameters (parameters and data), feedbacks (relationships), institutions (rules of the game), and goals as having an increasingly transformative impact on a social-ecological system. Ostrom (1990)[59] distinguished between two broad categories of public decisions: constitutional and allocational ones. The first, politically, shapes institutions (or policy instruments), including those for "commons" and for defining boundary conditions to, and interacting with, private (and corporate) decisions. The second, economically, uses institutions to modify benefit distribution within existing mandates. Jointly, these processes and their outcomes define governability[60] as a balance between the ambitions of all stakeholders and what can be operationalized. In the process of decision making, the bounded rationality that behavioral economics established experimentally[61] can be reconciled with (and be labeled more positively) the sociality concept[62], emphasizing (reference) groups, rituals, affiliation, status, and power as aspects. The ecosystem services concept suggests a one-way flow of benefits that are instrumental in achieving human goals. It appeals to rationality as the basis for decision-making. It has been augmented by an interest in relational

values of nature as a two-way process depending on and justifying investment, appealing to sociality as the basis for decision-making[63].

While footprints are defined as metrics, their relevance for decision-making depends on the feedback relationships that they help understand, the institutions that are using them in rules and incentives, and how they appeal to goals that they can help achieve. Footprints can represent instrumental values, but are also, in the metaphor used, relational and appealing to accountability.

In the four levels of the Meadows-based hierarchy (1999)[58] [Figure 4], the relationship between constitutional plus allocational decisions and the three categories of nature-specific values (instrumental, relational, and intrinsic) can be understood:

Parameters: Data, metrics, and expected (discounted) costs and benefits associated with quantified instrumental ecosystem services as value aspects interact with explicit, often binary decisions to accept or not accept proposed projects, investment in programs or contracts.

Feedbacks: Transactional values, open to bargaining, reduced risk of investment, potential social payoffs, reciprocity and status indicators interact with *efficiency*-oriented decisions on roles, cost and benefit allocation among multiple actors/stakeholders, and attention to implementation and transaction costs.

Institutions: Value aspects such as recognition, rules of the game, stewardship, eudaimonia (social well-being as a complement to individual hedonics[64,65]), group (club) membership, and avoiding conflict interact with constitutional ("*effectiveness*") decisions about rules of the game, boundaries to rights, in-group membership/exclusion and security (risk sharing).

Goals: "Invaluable", non-negotiable core values of respect, identity-related self-expression, ethics, and sovereignty/autonomy concepts, such as free and prior informed consent, interact with *equity* decisions on universal goals, ways to internalize externalities, intergenerational responsibility and ensure continuity.

Theories of place and change across scales

The urgently needed transformation towards sustainability that addresses current development deficits without trespassing planetary boundaries needs to combine climate change mitigation and adaptation. It has to reconcile the hierarchy of individuals nested in households nested in communities nested in sub-national jurisdictions nested in nation-states part of global humanity [the vertical axis in Figure 5], with the hierarchy of levels of "leverage" on complex, adaptive social-ecological systems based on Meadows (1999)[58]: data, feedbacks, institutions, and goals [the horizontal axis in Figure 5]. These latters are related to the "issue attention cycles" of policy change[63,66].

Footprints are in the "data" column in Figure 5 but can be expressed at national (including "average citizen of country X"), subnational emission intensity, community, or individual level. Footprints, or the activities used as the denominator, are part of feedbacks. They can become a target for roles and rules as far as they represent recognized goals - at the individual, national, or global scales.

The lower-left to upper-right diagonal in Figure 5 connects local action to global goals and vice versa [Figure 6A]. The cells above the diagonal imply that one first move up the hierarchy from individuals towards governance structures, before shifting from data to feedback processes, to institutions and goals; we tentatively describe this as the governance route. In its extreme form, it determines (in the ultimate top-

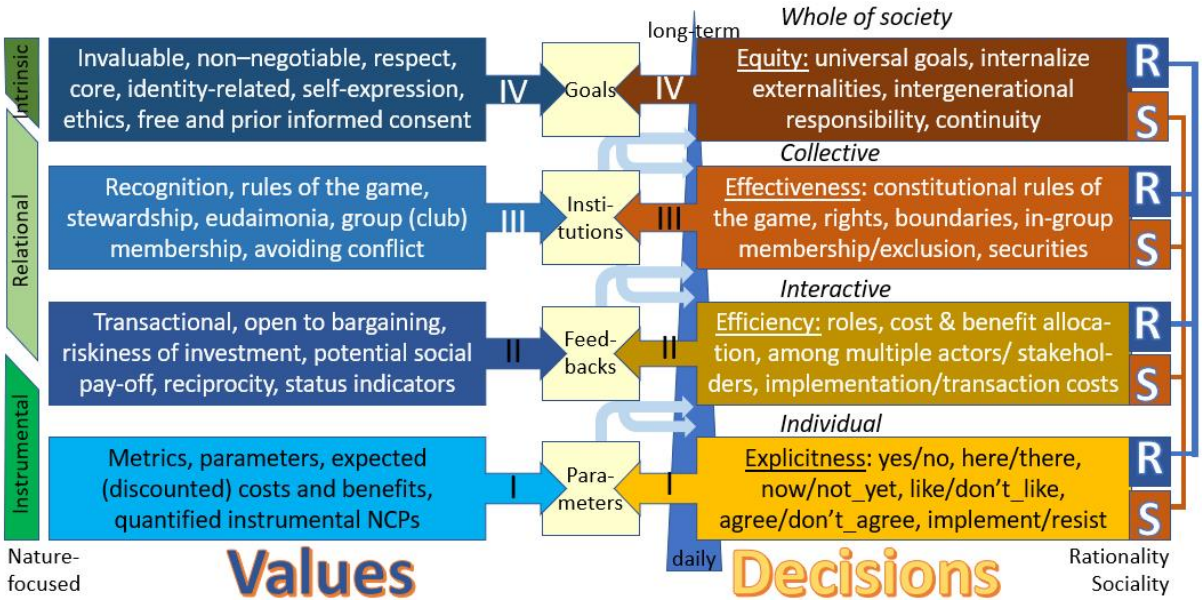

Figure 4. Values and decisions in their relation to parameters, feedbacks, institutions, and goals in the hierarchy of leverage points for complex, adaptive social-ecological systems[58].

	Data	Functional feedbacks	Rules&roles institutions	Goals
Global	SDG targets & indicators, IPCC, IPBES	Tipping points, Teleconnections, Scenario modeling	WTO, UNFCCC, CBD, REDD+, *0*-deforestation trade, C-tax	SDGs
National	National GHG communications, NDC reporting, Equity	Adjusted GDP, National Adaptation Plans, Disaster resp.	Parliaments, Laws, Ministries, Tax/subsidies, Invest	Constitution, Identity, Sovereignty, NDC, National development
Sub-national	Emission intensity CO_{2e}/GDP, OpCost, C-credits, Votes	Value addition, employment, equity, conflict, investment	Devolution, Land use plans & rights, Forest management, Permits	Green growth, Social-economic development, Land Use synergy
Community	Emission factors of land uses, Mimetrics, Risk estimates	Instrumental & relational value, Disaster vulnerability, Water	Co-management contracts, FPIC, Collective action, Commons	Resilient livelihoods, Respect, Eudaimonia, Spirituality
Individual	**Footprints,** Health, Awareness, Lifestyle choices, Wellbeing	Responsible consumption, certified products, coinvest	Human rights, education, resource use, tenure, jobs, health care, tax	Identity, Enterprise, Income, Voice, Basic needs, Security

Figure 5. Meadows-based hierarchy (data, feedbacks, institutions, and goals) across individual-to-global scales with examples of specific concerns in understanding and nudging societies (1999)[58]. CBD: Convention on Biological Diversity; FPIC: free and prior informed consent; GDP: gross domestic product; IPBES: Intergovernmental Science-Policy Panel on Biodiversity and Ecosystem Services; IPCC: Intergovernmental Panel on Climate Change; NDC: nationally determined contribution; OpCost: opportunity costs; REDD+: Reducing Emissions from Deforestation and (forest) Degradation; SDGs: Sustainable Development Goals; UNFCCC: UN Framework Convention on Combatting Climate Change; WTO: World Trade Organization.

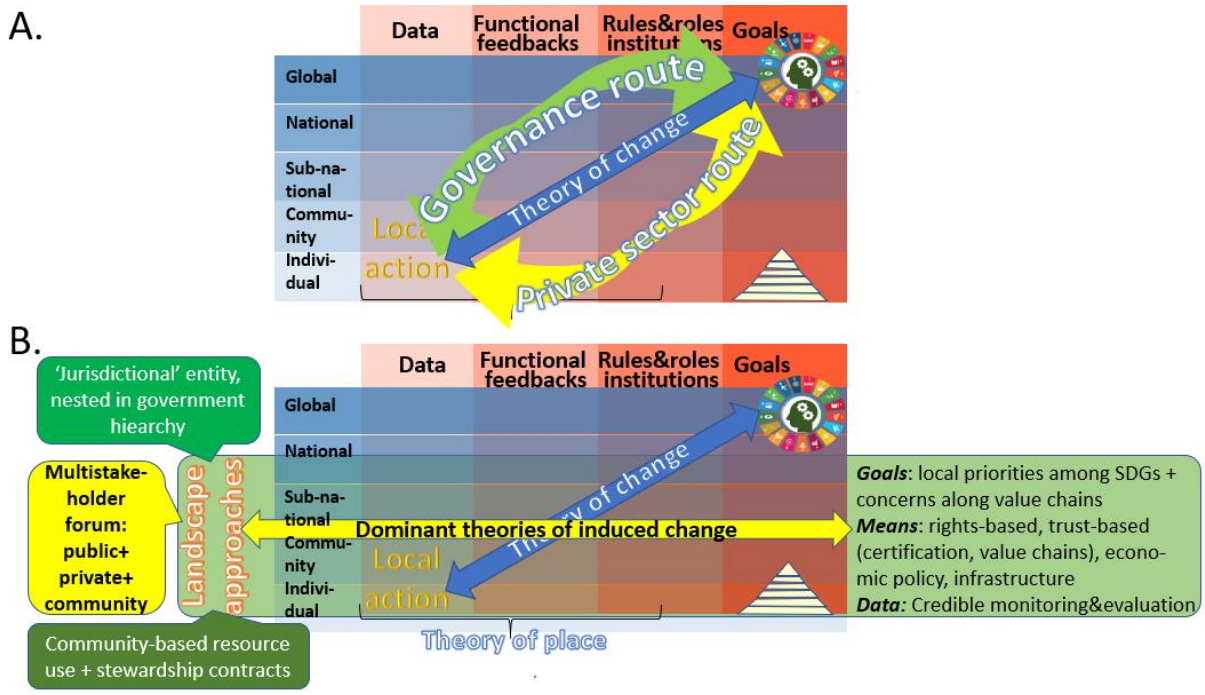

Figure 6. Variations and annotations of Figure 4 that clarify: (A) The dominant "theory of change" on the diagonal connecting local actions to global goals (and vice versa), while theories of place focus on the first two columns, the governance- and private-sector-based parts of theories of change; and (B) a dominant theory of induced change within "landscape approaches" to strengthen the interface between the lowest level of a government hierarchy and bottom-up collective action.

down way) the choices and actions individuals can take to achieve the highest-level goals. Footprints here are used in negotiating the fairness and efficiency of NDCs/individually determined contributions (IDCs) within and between countries.

The cells below the diagonal imply that one first shift from data to feedback processes, to institutions and goals, before moving up the hierarchy from individuals towards governance structures; we tentatively describe this as the private sector, market- or business-based route. In its extreme form (in the ultimate bottom-up way), it recognizes that individual goals drive individual choices and actions and that higher-level goals need to be framed to satisfy demand. Footprints here target the individual and collective decisions of producers, processors/traders, and consumers (IDCs).

In reality, a balance between top-down and bottom-up elements is negotiated across the scales. The global shift of governance systems towards more market-based policies implies attempts to redress the balance, rather than go from one to the other extreme, and has itself been subject to governability checks and balances in political-cultural contexts.

A popular theory of induced change[63] of the past decade has been one of several forms of landscape approach [Figure 6B] at the interface of the lowest jurisdictional level of formal governance structure and the local community, with its diversity of individuals[67-70]. It typically operates in a public-private-people partnership, with informal, negotiated rules, a focus on trial-and-error learning feedbacks, and goals that often are a selective subset of the SDG portfolio. However, according to practitioners, about half of the bottlenecks are caused at the points of interactions with national government agencies[71]. Bridging between the jurisdictional (rule setting) aspects of a connection with formal governance (and often enhanced

tenurial security), the private sector partners link to markets and the local community connects to aspirations in a social-cultural context (often including a sense of place or eudaimonia). Clarity on footprint data can provide a solid foundation for landscape-level negotiations with scientific credibility, social legitimacy, and political salience.

Theories of (induced) change concerning carbon footprints

The expectation, or theory of induced change, that transparent and credible footprints will change behavioral choices at individual and collective levels has not been easy to verify. One of the few critical impact studies thus far[72] found that grassroots-initiative members have a 16% lower total carbon footprint and 43% and 86% lower carbon footprints for food and clothing, respectively, compared to their "non-member" regional socio-demographic counterparts in Europe; they also have higher life satisfaction compared to non-members and are 11%-13% more likely to evaluate their life positively. Initiative members uncover lifestyle features that enable lower emissions and break the conventional link among emissions, income, and well-being.

Saujot *et al.*[73] (2020) analyzed explicit knowledge, mediation tools, and framing power as three main contributions that scenario articulation can make to policy decision-making. They discussed an apparent tradeoff between the framing power of integrating lifestyle changes in scenarios and the robustness and reliability of pathway production methodologies, which is a condition for their policy relevance. The nature of lifestyles, which reflect values and preferences and require a multidisciplinary approach, raises significant policy neutrality challenges and scientific challenges. Overcoming these challenges can lead to more policy-relevant pathways, starting with reliable footprint data including indirect effects on emissions and sink strength.

Slogans such as "choose nature, buy less" may appear to be an oxymoron (*contradictio in terminis*) for business models that interact with consumer preferences for responsible (and thus reduced) consumption. However, in a thus far limited niche market, businesses that emphasize efficiency, consistency, and more recently also sufficiency have opportunities to function[74]. Sufficiency aims at an absolute reduction of consumption levels and entails strategies such as decreasing purchases, modal shifts, product longevity, and sharing practices. Benefits for the individuals involved may be primarily social, as in the hedonic-eudaimonic contrast that Ancient Greek philosophers already recognized[64,65].

Discussion and ways forward

This perspective aims to present a framework for analysis that connects the various footprint concepts to theories of place, change, and induced change. Several emerging challenges are described in Figure 7.

Regarding the first question, the operational definition of carbon footprints, several consistency issues emerge. Measured changes in atmospheric GHG concentrations remain the primary consistency check for national accounting of fossil fuel plus land-use related GHG emissions, once structurally missing terms are added[19]. For carbon footprint concepts based on individuals, sectors, or businesses, the first question should be "does it add up?". Consistency issues may easily arise if both "production" and "consumption" actors are considered to make independent decisions, or if the attribution of blame is "to the other side". Similarly, EET remains a major challenge for national accounting systems, as importing countries do not accept them on their balance sheet. However, they are no problems for the lifecycle analysis of products underpinning individual footprints linked to consumer choices. Consequently, the sum of individual footprints can exceed the sum of national footprints.

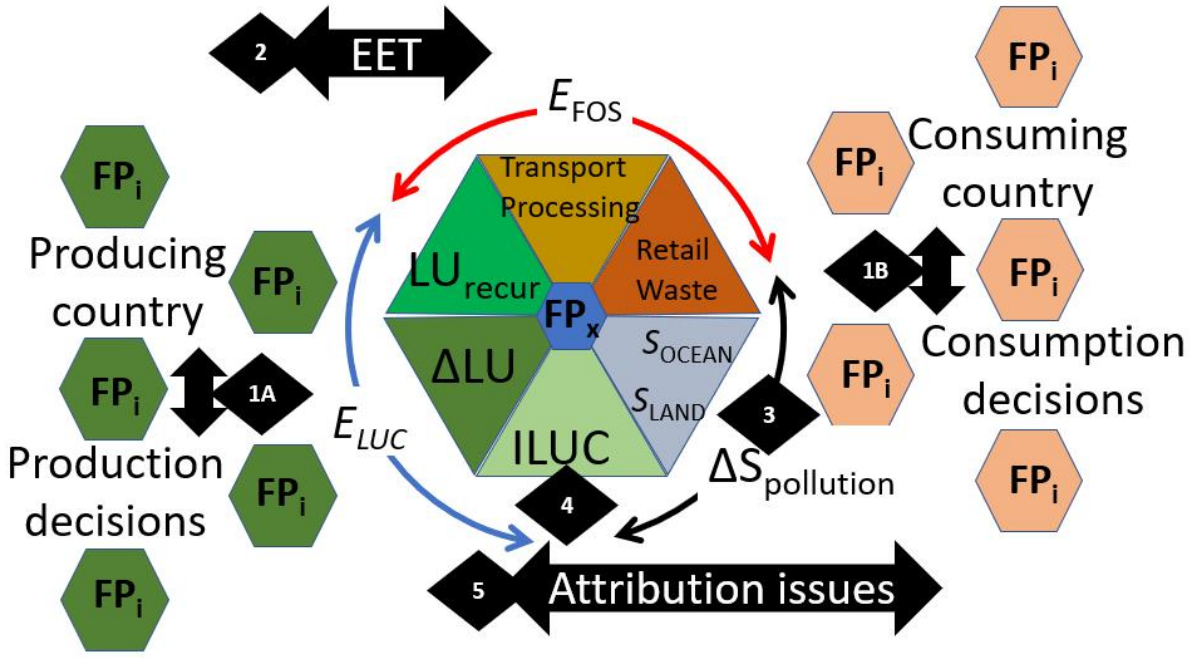

Figure 7. Visualization of challenges to the use of various footprint concepts (FP$_i$): (1) consistency checks between individual and national footprints across production and consumption; (2) accountability for emissions embodied in trade (EET); (3) incorporation of (avoided) impacts on sink strengths, e.g., based on pollution; (4) the indirect land-use change concept; and (5) further attribution issues in relation to multifunctional land uses.

A single footprint can relate to multiple policy goals at the policy level. For example, soil carbon and wetland preservation commitments have been made under three Rio Conventions: Land Degradation Neutrality (as part of the United Nations Convention to Combat Desertification), climate change (both mitigation and adaptation aspects in the UNFCCC), and biodiversity targets of the Convention on Biological Diversity, in different combinations across the 197 UN member states[75].

The fraction of current emissions that directly contribute to an increase in atmospheric concentrations of GHG, and thus the global climate change per unit emissions, keeps increasing with declining sink strength, with complex attribution issues in the comparison of historical, current, and future emissions. While global Carbon budgets consider emissions from fossil sources (E_{FOS}) plus those from land use (E_{LUC}), negative impacts (e.g., through pollution) on the sink strength of oceans (S_{OCEAN}) and terrestrial systems (S_{LAND}) are not included, and neither are efforts to avoid or repair such negative effects. However, they influence global climate change trajectories and are part of the international policy debate, e.g., regarding forests[76] and ecological restoration[77,78].

The concept of "indirect land-use change" (ILUC) is the most contested aspect within the land use emission category. It emerged in the discussion on biofuels when it was realized that new types of demand for agricultural products, beyond global food supply, would be partially responsible for expansion into new production areas (and thus for emissions associated with such expansion), even if the origin of specific products could be traced to low-emission areas (e.g., not linked to recent forest conversion)[79,80]. In practice, however, ILUC remains controversial as the attribution involves scales beyond the reach of individual producers or consumers and may need to shift to broader product categories. For example, ILUC concepts might attribute the consequences of increased demand to all vegetable oils, rather than a specific one such as palm oil, to reflect the exchangeability of commodities in the current food industry[81]. On the other hand,

the conclusion that coconut oil has, in comparison with other vegetable oils, a remarkably high negative biodiversity footprint[82] ignored that in the dataset, 93% of the negative biodiversity impacts were due to small island countries (with vulnerable biodiversity) that only produce less than 10% of global output[83]. Such skewed statistical distributions cannot be ignored in footprint analysis. Agricultural yield elasticity[84] and land sharing in multifunctional land use[85] form additional challenges; in practice, ILUC has not been integrated into standard accounting systems. Accounting for ILUC in footprint calculations depends on inferred causality and highly questionable product categorization. More comprehensive global trade data can help, but their interpretation remains highly political and contested.

On the second question, the way footprints are used as boundary objects in public and private decisions, the view has been expressed that the public appeal and rhetoric value of a single "ecological footprint" concept may well exceed the transparency and reproducibility of current operational metrics. For the carbon footprint component of the overall ecological footprint, the operational issues are less, but the carbon footprint may also be less actionable as tradeoffs with other component footprints exist. One such tradeoff is between carbon storage and water-saving[86]. When economic growth is included in the analysis[87], minimizing any single indicator may not lead to optimal results in the longer term[88,89]. In a similar debate, the water footprint concept has been challenged, with alternatives proposed that have natural vegetation and its water use as a point of reference[90].

Transparent attribution of emissions over drivers can be a strength of footprint quantification, as data on drivers can drive change - if used wisely[91]. Interfaces among footprints deserve attention, as renewable energy production can clash with biodiversity goals, with implications for transitioning to a green economy[92,93]. The interface of biodiversity loss and climate change[94] deserves a search for synergy beyond single footprint concepts. Co-benefits, tradeoffs, and thresholds have been discussed for mitigation policies targeting the agriculture, forestry, and other land use (AFOLU) sectors[95], as well as agroforestry as a land use at the interface[66,96,97]. Geopolitical questions of fairness between countries have their counterparts domestically, with many sectors in developing countries that have high carbon footprints state-owned or fully protected by the state.

Quantitative footprint metrics may be too complex for citizen audiences that prefer a simpler certification of meeting (or not) a set of thresholds for environmentally and socially responsible production, shifting blame to uncertified others[98-101]. Oversimplified policies do not do justice to the complexity of social actors interacting with the unsustainability of agriculture[102]. Global lessons from payment and incentive schemes have suggested that a location-specific form of co-investment in ecosystem services is more feasible than fully result-based schemes using a single metric, such as a carbon footprint[103]. The motivation of national governments to engage in NDCs and voluntarily commit to further reducing emissions from land use may be based on protecting export earnings rather than on climate-related payment schemes as such[104].

Finally, several ideas emerged on how footprint concepts might be improved, including by further research and synthesis. Multifunctionality of land use, a major pathway to reconcile human ambitions and our planet's biocapacity, is still a challenge for common accounting and footprint systems. Carbon footprints may correlate with biodiversity footprints[105], but only partially; however, theories of change are challenged without synergy among ecological footprint components. The irony may be that multifunctional land uses that can contribute to simultaneously addressing multiple problems are not easily assessed, given the various attribution issues mentioned under the first question. This includes the wide range of agroforestry systems that are relevant at the interface of climate change mitigation and adaptation, but not superior in either issue considered separately[90].

CONCLUSIONS

Regarding our first question ("How is the operational definition of carbon footprints related to consistent accounting for GHG, emissions?"), four conclusions emerge:

1. Measured changes in atmospheric GHG concentrations remain the primary consistency check for national accounting of fossil fuel plus land-use related GHG emissions as well as for carbon footprint concepts based on individuals, sectors, or businesses; for any new type of footprints, the first question should be "does it add up?".

2. EET remain a major challenge for national accounting systems but are no problem for Lifecycle analysis of products underpinning individual footprints linked to consumer choices.

3. Negative impacts on oceanic and terrestrial C sinks, or positive effects of reducing pollution or land cover change affecting sinks, remain outside current national accounting as well as common footprint concepts, yet influence global climate change trajectories.

4. ILUC in footprint calculations depends on inferred causality and product categorization that are highly questionable, rather than addressing the drivers.

Regarding the second question ("How are footprint concepts used as boundary objects in public and private decision making?"), we conclude:

5. The public appeal and rhetoric value of footprint concepts may well exceed the transparency and reproducibility of current operational metrics.

6. Carbon footprints as an aspect of human appropriation of net primary productivity (HANPP) are correlated with water footprints and biodiversity impacts that deserve joint responses by consumers, individually and collectively.

Finally, on Question 3 ("How might footprint concepts be improved?"), we conclude:

7 Multifunctionality of land use, a major pathway to reconciling human ambitions and our planet's biocapacity, is still a challenge for common accounting and footprint systems. Other than GHG exchange with the atmosphere, functions that involve lateral flows have specific scaling rules that need to be used to link local to global scales and *vice versa*. Follow-up research can contribute by: (A) testing and improving consistency among footprint estimates, so that they add up to global net emissions; (B) analyzing synergy, tradeoffs, and interactions among various components of an overarching ecological footprint (including aspects with -non-area based scaling); (C) exploring boundary work and the way footprint data are used in societal change; or (D) zooming in on the specific challenges of footprint accounting for multifunctionality of land use in the face of the UN Sustainable Development Goal agenda.

DECLARATIONS

Authors' contributions

Made contributions to the conception and design of the study: van Noordwijk M, Pham TT, Leimona B
Performed data analysis interpretation and writing of the manuscript: van Noordwijk M, Pham TT, Leimona B, Duguma LA, Baral H, Khasanah N

Provided material support: Dewi S, Minang PA

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All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate
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Not applicable.

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Review

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Artificial intelligence and soil carbon modeling demystified: power, potentials, and perils

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Abstract

The global soil carbon pool has been estimated to exceed the amount of carbon stored in the atmosphere and vegetation, though uncertainties to quantify below-ground carbon and soil carbon fluxes accurately still exist. Modeling soil carbon using artificial intelligence (AI) - machine learning (ML) and deep learning (DL) algorithms - has emerged as a powerful force in the carbon science community. These AI soil carbon models have shown improved performance to predict soil organic carbon (SOC) storage, soil respiration (R_s), and other properties of the global carbon cycle when compared to other modeling approaches. AI systems have advanced abilities to optimize fits between inputs (geospatial environmental covariates) and outputs (e.g., SOC or R_s) through advanced pattern recognition, learning algorithms, latent variables, hyperparameters, hyperplanes, weighting factors, or multiple stacked processing (e.g., convolution and pooling). These machine-oriented applications have shifted focus from knowledge discovery and understanding of ecosystem processes, carbon pools and cycling toward data-driven applications that compute digital soil carbon outputs. The purpose of this review paper is to explore the emergence, applications, and progress of AI-ML and AI-DL algorithms to model soil carbon storage and R_s at regional and global scales. A critical discussion of the power, potentials, and perils of AI soil carbon modeling is provided. The paradigm shift toward AI modeling raises questions how we study soil carbon dynamics and what conclusions we draw which impacts carbon science research and education, carbon management, carbon policies, carbon markets and economies, and soil health.

Keywords: Soil carbon, soil organic carbon, soil respiration, artificial intelligence, machine learning, deep learning, artificial neural networks

INTRODUCTION

The global soil carbon (C) pool has been estimated to exceed the amount of carbon stored in the atmosphere and vegetation[1-3], though uncertainties to quantify below-ground carbon accurately still exist. According to Scharlemann *et al.*[2] (2014), the total estimated global SOC stock mean is about 1500 Pg C with highest soil organic carbon (SOC) stored in boreal moist (~350 Pg C), cool temperate moist (~210 Pg C), and tropical moist ecosystems (~150 Pg C). However, the uncertainty of studies that assessed soil carbon stocks (0-1 m) is considerable ranging from 504 to 3000 Pg C among 27 different global assessments[2]. These uncertainties are due to the large variability in SOC, changing climate and environmental conditions that impact soil C dynamics, different methods and modeling approaches to estimate SOC, as well as data limitations and overuse of legacy data[4]. A substantial proportion of SOC has been measured only in the topsoil (< 30 cm) with sparser observations in the subsoils that have been estimated to store about half of the global soil carbon[5-7].

The spatial and temporal variability of soil carbon storage, soil carbon sequestration (SCseq), and carbon fluxes are critically important to address soil health, soil security, food security, regenerative agriculture, and climate-smart soil conservation management. Soil carbon provides an ecosystem service implicated in numerous soil functions, such as nutrient regulation and mitigation of greenhouse gas (GHG) emissions that are pivotal to emergent carbon economies and markets. The significance of soil carbon in global biogeochemical cycles is profound. To sustain multiple soil functions and preserve soil health and soil security several quantification methods, among them artificial intelligence (AI), have been utilized at escalating spatial scales. The purpose of this review paper is to explore the emergence, applications, and potential of AI - machine leaning (ML) and deep learning (DL) algorithms - to model soil carbon storage and soil respiration (R_s) at regional and global scales. A critical discussion of the power, potentials, and perils of AI soil carbon modeling is provided.

Soil carbon assessments and dynamics

Soils are considered net sinks for soil carbon with global net sequestration estimated at 1 Pg C yr^{-1}[8]. To enhance SOC sequestration agricultural practices, such as no-tillage, conservation tillage or reduced tillage, and land use conversions have been suggested to offset GHG emissions[9,10]. Estimates suggest that land use contributes about 25% of total global GHG emissions (mainly CO_2, CH_4 and N_2O) with 10%-14% directly from agricultural production, specifically via GHG emissions from soils and livestock management, and another 12%-17% from land cover change, including deforestation and conversion of grassland[11]. Specifically, emissions of N_2O and CH_4 from soils with high greenhouse warming potentials with 280-310 and 56-21 times that of CO_2 (20-100 years, respectively) are implicated in soil carbon gains and losses. Six *et al.*[12] (2004) found in a global meta-analysis that in no-tillage agricultural systems SCseq observations were positive +195, +213, +222 kg C ha^{-1} yr^{-1} in the topsoil in humid climate after 5, 10, and 20 years of measurements, respectively. However, initial SOC losses due to increased GHG emissions from soils were observed in the topsoil in temperate dry climate with SCseq observations of -306, -37, and +97 kg C ha^{-1} yr^{-1} after 5, 10, and 20 years. Sun *et al.*[13] (2020) in a global meta-analysis in no-tillage systems assessed that SCseq varied between -2.75 to +3.99 Mg C ha^{-1} yr^{-1} (0.35 ± 0.05 standard error) in the topsoil with climate dependent sequestration rates. However, besides climatic factors such as mean annual temperature and mean annual precipitation[13-16], other factors such as soil texture[17], crop frequency and legumes cover crops[18] can pose major influence on SCseq in no-tillage or conservation tillage systems. Agricultural-based GHG mitigation practices were estimated with wide ranges dependent on assumptions of C pricing [$US20 to US100 per Mg CO_2(eq)] up to a maximum technical potential: (1) biochar application: 1.0-1.8 Pg CO_2(eq) yr^{-1}; (2) grazing land management: 0.3-1.6 Pg CO_2(eq) yr^{-1}; (3) cropland management: 0.3-1.5 Pg CO_2(eq) yr^{-1}; (4) enhanced root phenotypes: about 1 Pg CO_2(eq) yr^{-1}; (5) restore degraded land: 0.1-0.7 Pg CO_2(eq) yr^{-1}; (6) restore Histosols: 0.3-1.3 Pg CO_2(eq) yr^{-1}; (7) rice management:

0.2-0.3 Pg CO_2(eq) yr^{-1}; (8) water management 0-0.07 Pg CO_2(eq) yr^{-1}; and (9) retirement of land (setaside): 0.01-0.05 Pg CO_2(eq) yr^{-1}[9,14].

Numerous science-informed initiatives and programs to enhance SCseq paint an optimistic carbon future. One prominent initiative, the "4 per Mille Soils for Food Security and Climate" initiative was launched at COP21 in 2015 aiming to increase global soil organic matter stocks by 4 per 1000 (or 0.4%) per year as a compensation for the global emissions of GHGs by anthropogenic source[19]. According to Minasny *et al.*[19] (2017), applying the 4 per mille in the top 1m of global agricultural soils, SOC sequestration was estimated between 2-3 Gt C yr^{-1}, which would effectively offset 20%-35% of global GHG emissions. Though White *et al.*[20] (2018) disputed that such global GHG offsets are gross overestimates and the 4 per mille rate of SCseq is not feasible. Other criticism raised in regards to the "4 per Mille Soils" initiative involve poor and inconsistent calculation of target and GHG emissions, the implausibility of upscaling results to global scale, and the fact that soil carbon storage is limited and non-permanent[21]. Poulton *et al.*[22] (2018) measured SOC increases at > 7‰ per year (0-23 cm depth) in 65% on long-term experimental plots at Rothamsted UK which approximated about 4 ‰ per year (0-40 cm depth). Though it was pointed out that practices favoring SOC sequestration are already implemented in many agro-ecosystems, farmers may not have the necessary resources (e.g., insufficient manure), and some practices may be uneconomic or limit crop yield which would be undesirable to achieve global food security. van Groenigen *et al.*[23] (2017) critiqued that available nitrogen and phosphorus is insufficient to achieve 4 per mille increase of soil carbon per year. Baveye *et al.*[24] (2018) cautioned that enhanced mineralization on addition of easily decomposable carbon (i.e., the priming effect) could potentially release even more CO_2 from soils, and amplified temperature increases and/or microbial activity may release large amounts of CO_2 from soils in the future. The question whether SOC storage can be increased by 0.4% (= 4 ‰) per year is a sensational hyperbole or realistic can only be answered through accurate global soil carbon assessments. The advancements in AI-soil carbon modeling offer opportunities to improve SOC stock, SCseq, and GHG emission assessments.

Artificial intelligence: machine learning and deep learning

Artificial intelligence emerged during WWII (1939-1945) when Alan Turing invented the bombe machine to crack the "Enigma" code used by Germans, which was the foundation for ML. In 1950 two undergraduate students (Marvin Minsky and Dean Edmonds) build the first neural network computer and in 1959 Donald Hebb conceptualized the Hebbian learning algorithms with many other algorithms to follow. The first adoption of the term "AI" occurred at the Dartmouth conference in computer science in 1956. But it was not until the 1990s onward when the increase of computational power enabled the blossoming of AI algorithms and integration of AI in science, technology, engineering, and mathematics research. Since the early 2000s the Big Data era brought forth AI-geoscience, AI-smart agriculture, and other AI-ML applications with more recent applications of AI-DL methods[25].

According to Russell and Norvig[25] (2020), AI is concerned with not just understanding but also building intelligent entities - machines that can compute how to act effectively and safely in a wide variety of novel situations. Machine learning refers to machines and systems that can learn from experience supplied by data and algorithms with a model training (or calibration phase) followed by a model validation phase with independent data. Machine learning is the science of getting computers to act without being explicitly programmed. In essence, machine-driven recognition of patterns and structures in data are revealed through "brute force fitting" between input and output data. Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction[26]. Deep learning is similar to ML because the former is still just another methodology of statistical learning that extracts features or attributes from raw data sets. But the advancement of DL algorithms is that they automatically extract features for classification with multiple layers of adjustable

computing elements (e.g., hidden nodes and hidden layers) with sophisticated learning algorithms that fit inputs and outputs[25]. Artificial neural networks (ANN) are inspired by the biology of the human brain, specifically the organic interconnections between neurons. The human brain analyzes information it receives and identifies it via neuron connections according to past information it has stored in memory. The brain does this by labeling and assigning information to various groups, and it does this in nanoseconds. Similarly, when a system receives an input, the DL algorithms train the artificial neurons to identify patterns and classify information to produce the desired output. But, unlike the human brain, ANNs operate via discrete layers, connections, and directions of data propagation[25,27].

AI MODELING OF SOIL CARBON STORAGE AND DYNAMICS

In the discipline of pedometrics, the adoption of AI algorithms in digital soil mapping emerged in the early 2000s. From 2015 onward advanced AI soil models were developed in the domains of proximal soil sensing and soil carbon modeling using large environmental data hypercubes[28]. A comprehensive review of AI-ML algorithms applied in digital soil mapping, including soil carbon modeling, was provided by Khaledian and Miller[29] (2020), a review of DL for digital soil mapping was provided by Padarian *et al.*[30] (2019), and a review of DL in agriculture was provided by Kamilaris and Prenafeta-Boldú[31] (2018). Recently, a comprehensive review of ML and remote sensing methods to estimate various soil indicators was presented by Diaz-Gonzalez *et al.*[32] (2022). In this section I present a brief overview of some of the most prominent AI methods that have been employed in soil carbon modeling which informs a critical discussion of the power, potentials, and perils of these methods.

Soil carbon AI models are build using hypercubes of environmental covariates as inputs [Figure 1 and 2A]. These environmental covariates represent the domains of soils (S), topography (T), ecology (E), parent material or lithology (P), atmosphere or climate (A), water or hydrology (W), biota with vegetation and organisms (B), and human activities/management (H)[4,33-35] similar to the conceptual framework of SCORPAN (McBratney *et al.*[36] 2003). The STEP-factors are relatively stable across the human lifetime, while the AWBH-factors are dynamic in space and across time. Each of these factors can be quantified through a set of variables. For example, the S factor can be characterized by soil data such as soil texture, pH, soil taxonomic class, cation exchange capacity, *etc.* derived from legacy soil maps or databases, proximal soil sensing (e.g., visible-near infrared spectroscopy, VNIR; mid-infrared spectroscopy), gamma ray sensing, and remotely sensed soil moisture data. The factor A may be populated by climatic data such as long-term average of mean annual precipitation, seasonal variation of minimum and maximum temperature, and long-term solar radiation, while B can be populated by satellite-derived land use/land cover maps, vegetation indices like the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI) derived from satellite data, biodiversity, and habitat data. The factor H may be populated by variables from the social, cultural, economic, and political domains (e.g., greenhouse gas emission data, land management data such as tillage operations, and fertilization amount and type). The aim is to populate the STEP-AWBH factors with environmental geodata that influence the carbon cycle. Xiong *et al.*[37] (2014) exemplified the STEP-AWBH model and multiple AI-ML methods in Florida, United States, to develop prediction models for SOC stocks.

Commonly applied ai algorithms to model soil carbon

Classification and Regression Trees (CART) were introduced by Breiman[38] (1984) and have served as foundational approach onto which other ML have built on [Figure 2B]. According to Breiman[38] (1984), CART involves constructing a set of decision trees on the predictor variables. The trees are grown by repeatedly stratifying the dataset into successively smaller subsets (child node) with binary splits based on a single categorical or continuous predictor variable. The splitting procedure is applied until the best split is

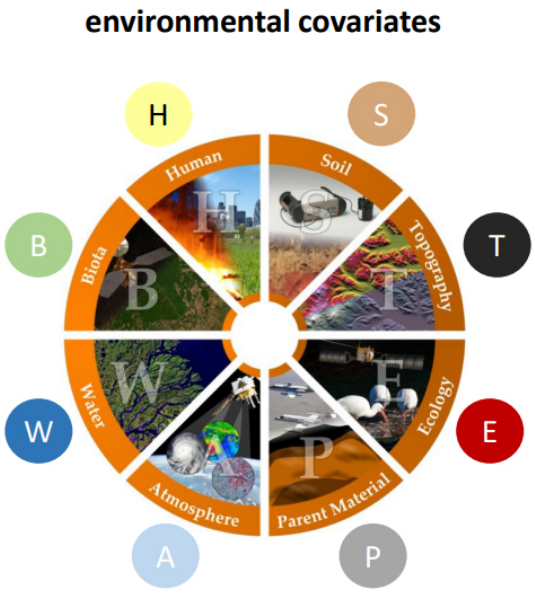

Figure 1. Environmental covariates from the domains of soils (S), topography (T), ecology (E), parent material (P), atmosphere (A), water (W), biota (B), and human (H). Each of these domains is represented by a wide variety of variables that facilitate AI-soil carbon modeling (image is courtesy of S. Grunwald).

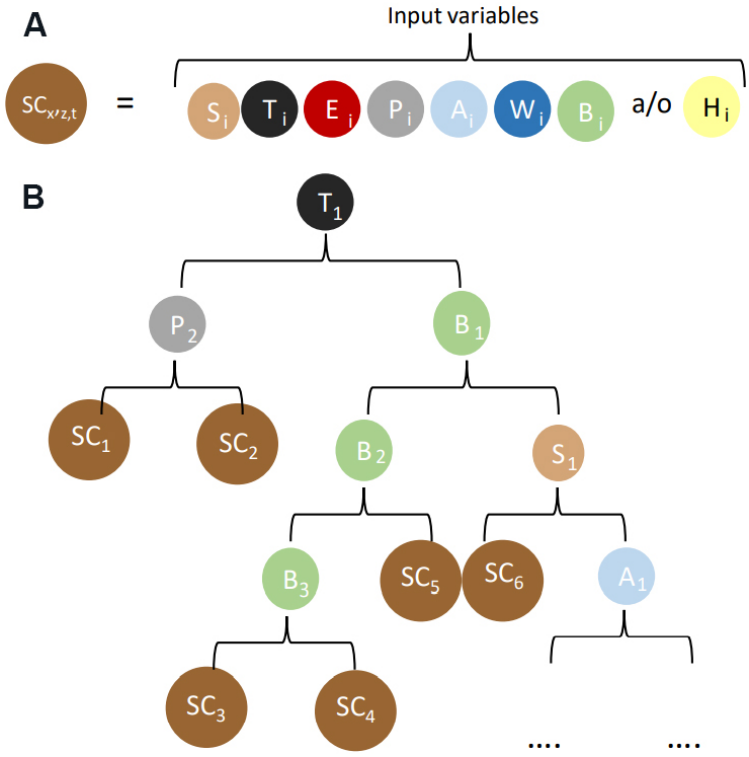

Figure 2. (A) Functional relations between environmental covariates (STEPAWBH factors with variables i = 1, 2, 3, ..., N). SC denotes a variable of the carbon cycle (target output), for example, soil organic carbon (SOC) stock, SOC density, total soil carbon, soil respiration (R_s), soil carbon sequestration (SCseq), soil carbon pools, soil carbon fractions, *etc.* x is spatial location (with xy coordinates; or latitude/longitude); z is soil depth with z = 1, 2, 3, ..., Z; and t is time with t1, t2, t3, ..., T. (B) AI model predicting soil carbon (SC) from environmental covariates. Simplified representation of a machine learning ensemble tree method (e.g., Classification and Regression Trees, CART, or Cubist) with tree branches and data splits.

chosen based on the one that maximizes the response into two homogenous groups (i.e., minimizing variability within each child node)[39].

A variant of CART is **Bagged Regression Trees (BaRT)** which is an ensemble decision tree method that involves the averaging of several individual trees to acquire a final prediction. Individual regression trees have shown somewhat erratic modeling results where small changes in input variables produces large differences in output trees[40,41]. This limitation of individual CART is overcome by bagging (i.e., bootstrap aggregation) in BaRT. Bagging is an ensemble learning method that is commonly used to reduce variance within noisy datasets. In bagging, a random sample of data in a training (or calibration) set is selected with replacement, which means that the individual data points can be chosen more than once. Thus, the procedure grows a regression tree from each bootstrap sample. To obtain the overall final prediction for a target variable the results of each individual tree are averaged[42].

Boosted Regression Trees (BoRT) belong to the Gradient Boosting Modelling family, which is one among many methods to predict the function F that maps the values of a set of predictor variables x = {x1,..,xp} into the values of the output variable y, by minimizing a specified loss function L. In BoRT the prediction is performed using boosting[43]. In general, boosting methods are applied to significantly improve the performance of a given estimation method, by generating instances of the method iteratively from a training data set and additively combining them in a forward "stagewise" procedure. BRT uses a specialized form (for regression trees) of the Stochastic Gradient Boosting[44]. The gradient boosting machine algorithm was described in detail by Friedman[44] (2001). The regression tree algorithm developed by Breiman[38] (1984) served as the foundation of BoRT, which has shown to boost accuracy compared with simple regression trees, mainly due to its stochastic gradient boosting procedure aiming at minimizing the risk of overfitting and improving its predictive power[45]. According to Hastie *et al.*[41] (2009), in BoRT trees are grown sequentially with each tree grown using the information from previously grown trees. The BoRT algorithm facilitates fitting the model to the data in an iterative process. At each iteration, individual regression trees, are fitted on a fraction (namely the bag fraction) of the dataset sampled without replacement. The main parameters for fitting BRT are the tree size and the learning rate.

Random Forest (RF) is a widely used ML method consisting of an ensemble of randomized classification and regression trees[38,46]. The RF algorithm grows different trees by randomly and repeatedly selecting predictor variables and training cases to develop a random population of trees. The algorithm grows an ensemble of regression trees based on binary recursive partitioning, where the predictor space at each tree node is partitioned based on binary splits on a subset of randomly selected predictors[47]. The output of RF is the average of individual tree predictions. It has been shown that the RF algorithm can be very efficient, especially when the number of descriptors is very large[48]. The RF model is capable of simultaneously handling categorical and continuous variables, as well as complex high-order variable relationships such as nonlinearity and interaction effects. Conditional quantiles can be inferred with **Quantile Regression Forests (QRF)**, a generalization of RF. Quantile regression forests is a non-parametric technique used to estimate the conditional quantiles of multidimensional predictor variables. The benefits of QRF is its ability to predict more accurate results for the conditional distribution of the response variable[49].

The **Support Vector Machines (SVM)** applies a projection of the input data into a high-dimensional feature space using a valid kernel function and then it uses a simple linear regression within this enhanced space[50]. This resulting linear regression function in the high-dimensional feature space corresponds to a non-linear regression in the original input space [Figure 3A]. In the new hyperspace, SVM aims to construct an

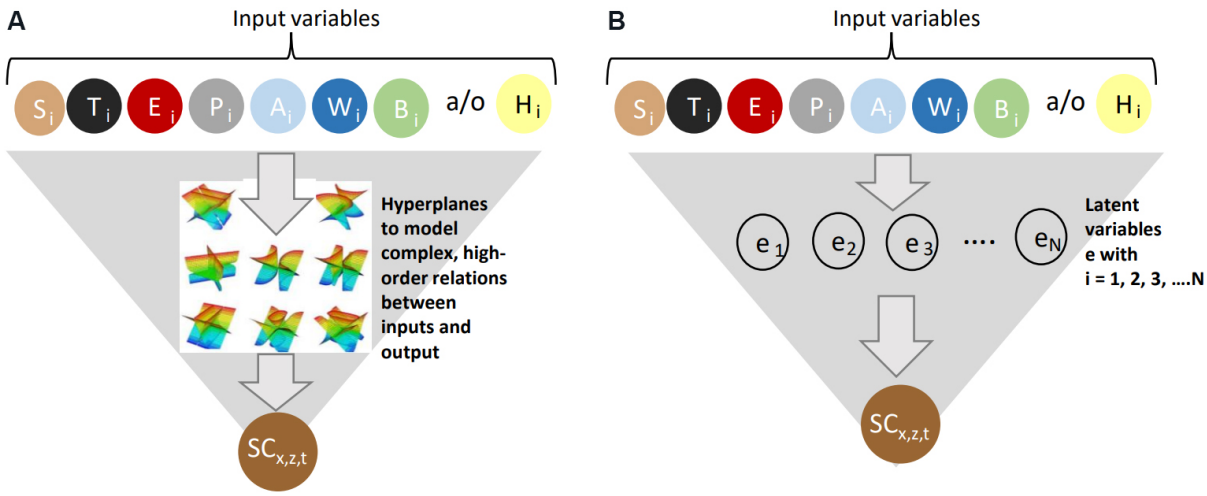

Figure 3. AI models predicting soil carbon (SC) from environmental covariates. Idealized model representation of (A) support vector machines (SVM), and (B) partial least squares regression (PLSR).

optimal hyperplane that separates classes and creates the widest margin between their data (i.e., classification), or that fits data and predicts (i.e., SVR) with minimal empirical risk and complexity of the modelling function[51,52]. **Support Vector Regression (SVR)** is a generalization of SVM and is used for nonlinear classification and regression[53]. The ε-SVR uses a loss function to define the borders (hyperplane) of the regression function. Hence the regression function lies between ± ε (maximum error). Therefore, the loss is equal to 0 if the difference between the predicted and measured values is less than ε[51].

The **Partial Least Square Regression (PLSR)** was developed by Wold[54] (1975) in econometrics and has since been widely used in many disciplines, including soil science and pedometrics. The PLSR algorithm relates the response variable (e.g., SOC) and a large number of highly collinear predictor variables (e.g., environmental covariates) through a multivariate model to identify successive orthogonal principal components (latent variables) that maximize the covariance between the response and predictor variables (Garthwaite[55], 1994). These latent factors are defined as linear combinations constructed between input variables (i.e., predictors) and response variables, such that the original multidimensionality is reduced to a lower number of orthogonal factors to detect the structure in the relationships between predictor variables and between these latent factors and the response variables [Figure 3B]. The extracted factors account for successively lower proportions of original variance[56,57]. According to Carrascal *et al.*[56] (2009), PLSR is especially suited to analyzing a large array of interrelated predictor variables (i.e., variables that are not truly independent). Soil carbon often covaries with other soil and environmental properties, and thus, PLSR is well suited to handle such multicollinearities.

The **Cubist (Cub)** algorithm is a decision tree model with piecewise linear models[58]. Cubist partitions the response data into subsets within which their characteristics are similar with respect to the predictors. A series of if-else conditions define rule-based partitions which are then arranged in a hierarchy. The simplest partition is based on only one predictor, though often multiple predictors are used to form a partition which are expressed in form of regression equations making models transparent for users [Figure 2B].

In general, an **ANN** is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use [Figure 4A]. The benefits of ANN are (1) ability to learn and therefore generalize; (2) solve complex problems (e.g., complex

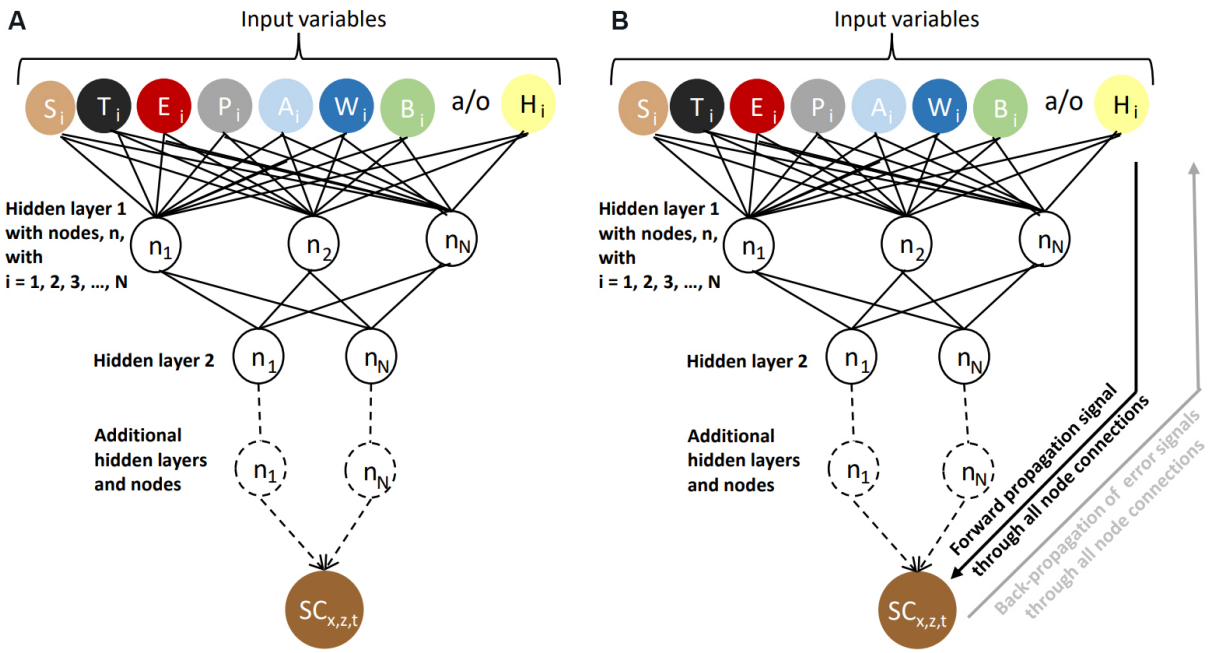

Figure 4. AI models predicting soil carbon (SC) from environmental covariates. Idealized model representation of (A) feedforward artificial neural network (fANN) and (B) backward propagation artificial neural network (bANN).

soil carbon-environmental relationships); (3) model linear, nonlinear, and high-order relations between inputs and outputs; and (4) provide input-output mapping (i.e., supervised learning)[59]. The **backpropagation ANN algorithm** is a multi-layer perceptron neural networks (i.e., a MLP neural nets) [Figure 4B]. The architecture of the MLP neural nets consists of input, one or multiple hidden, and output layers, each with a set of interconnected nodes (neurons) working in parallel to fit input data and output values through adjusting weights and cost function[60]. Hidden nodes represent abstract factors with no physical connection to ecosystems (i.e., the outside world). The purpose of hidden nodes is to transfer information from the input nodes to the output nodes. Backpropagation supervised learning is based on the error-correction learning rule. It consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass an activity pattern (input vector) is applied to the sensory nodes of the network and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the network are all fixed, while during the backward pass the synaptic weights are all adjusted in accordance with an error-correction rule. The actual response of the network is subtracted from a desired (target) response to produce an error signal. This error signal is then propagated backward through the network. During this backward pass the synaptic weights are adjusted to make the actual response of the network move closer to the desired response in a statistical sense[59]. Various backpropagation-based implementation methods including structure-fixed training and structure-adaptive training methods as well as sparse representation and dictionary learning methods were described in Wythoff[61] (1993). **Recurrent neural networks (RNN)** are algorithms for sequential data along a temporal sequence. These kind of algorithms remember its input due to an internal memory[59]. For example, RNN are suitable for soil carbon dynamics modeled over many years (e.g., SCseq modeling after conversion from conventional to no-tillage or modeling of SCseq and global climate change).

Convolutional Neural Networks (CNN) is a DL AI method that was described in detail by[27] for image, speech, and time series analysis. According to LeCun *et al.*[26] (2015), DL discovers intricate structures in complex and large datasets by using a backpropagation algorithm. A DL architecture is a multilayer stack of simple modules, all (or most) of which are subject to learning, and many of which compute non-linear input-output mappings. Deep neural networks exploit the property that many natural signals are compositional hierarchies, in which higher-level features are obtained by composing lower-level ones. Importantly, CNNs use convolutional layers to detect local conjunctions of features from previous layers with the pooling layer merging semantically similar features into one. CNNs are suited for SOC predictive modeling from environmental covariates because they allow convolution filtering (e.g., a 3 × 3 window filter) and pooling of multiple layers. Each unit of the feature map is linked to local patches in the feature maps of the previous layer through a set of weights; and the local weight sum is emulated through a non-linear transfer function. CNN allow use of data augmentation to represent soils within a region, which can reduce overfitting and also improve prediction accuracy. Another benefit of CNN is to predict different soil depths simultaneously in a model inherently taking into account the depth correlation of soil attributes. This allows to improve the prediction of SOC or other soil properties in deeper layers, which has been a common problem in other soil modeling studies with ML algorithms[30].

AI applications to model soil carbon storage and soil respiration

AI-based soil carbon stock and content modeling

Soil carbon models computed by AI methods allow explicit and rigorous evaluations computing various error metrics using cross-validation and/or validation with independent datasets. Another benefit of AI is the provision of spatially-explicit uncertainty assessment of soil carbon estimates [Table 1]. Commonly used evaluation metrics of soil carbon AI models include the coefficient of determination (R^2), root mean squared error (RMSE), mean absolute prediction error (MAE), residual prediction deviation (RPD), ratio of performance to inter-quartile range (RPIQ), and Lin's concordance correlation coefficient[62-64]. The RPIQ and RPD metrics take the variability of data into consideration though these metrics are often underreported in soil carbon studies. According to Bellon-Maurel *et al.*[62] (2010) a RPIQ < 1.00 is unreliable, 1.00 to < 1.60 is fair, 1.60 to < 2.00 is acceptable, and > 2.00 is excellent. For the RPD, a value of < 1.00 is not reliable, 1.00 to 1.40 is fair, 1.40 to < 2.00 is acceptable, and > 2.00 is considered excellent[65,66]. Several of the SOC AI models in Table 1 achieved excellent RPIQs, for example, Peng *et al.*[67] (2015) with RPIQ of 2.50 in Denmark, Ross *et al.*[68] (2019) with RPIQ of 2.10 in the southeastern U.S. The SOC models in Florida, U.S. achieved excellent RPDs up to 2.15[66] and acceptable RPD of 1.70[67], RPDs between 1.43 to 1.54 in Florida, U.S.[37] and between 1.32 and 1.88 in Florida, U.S.[69]. Regional soil carbon models derived from AI-ML and AI-DL methods showed a wide range of poor to excellent model fits with R^2 of 0.08[53] to 0.91[70], respectively [Table 1]. The RMSE results for soil carbon models shown in Table 1 need to be interpreted relative to the SOC observation range in the study region and the units of the specific soil carbon attribute. Some studies only predicted SOC concentrations, and not SOC stock, limiting interpretability in terms of soil health, soil functionality and the amount of carbon stored in soils. The model performance metrics suggests that in numerous of these studies there was substantial unexplained variability possibly linked to data limitations and/or sample densities.

Some sample sizes were small with only 220 soil samples in a study in Kenya[71], while other studies showed high numbers with 29,927 samples in East China[72], 70,803 in Australia[73], and about 150,000 soil profiles in a global study[74]. The environmental covariates (STEP-AWBH) incorporated in AI models varied widely with sometime ambiguous reporting, thus, interpretations which and how many covariates were incorporated in AI models is difficult. Though the H factor was rarely populated in most SOC models suggesting that land management, fertilization levels, GHG emissions, economic data, and other human and cultural dimensions are not given sufficient attention.

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Table 1. Examples of strategically selected artificial intelligence (AI) methods to predict gridded soil organic carbon (SOC). Studies were selected to represent different geographic soilscapes, sample sizes, region sizes, and AI methods. Only the best performing models are reported from different studies

Target variable (soil depth, cm)	Units SOC	Location (approx. size, km^2)	Soil samples	Environ-mental covariates (number of variables, *n*)	SOC observations			AI method[1]	Eval	Independent validation[2]				Ref.
					Min.	Mean	Max.			R^2 or CCC	RMSE	RPD	RPIQ	
SOC stock (0-30)	Mg ha^{-1}	Eastern Mau Forest Reserve, Kenya, East Africa (650)	220	STE-AB (*n* = 19)	41.99	103.15	193.42	ANN RF SVM	Val.	0.61 0.53 0.64	15.46 17.57 14.88	- - -	- - -	Were *et al.*[71] (2015)
SOC content (0-30)	%	Skjer basin, Denmark (2500)	328	STEP-AWB	0.70	3.70	31.60	Cub (upland model C)	Val.	0.66	0.59	1.70	2.50	Peng *et al.*[67] (2015)
SOC stock (0-30; sampled at 5 increments)	Mg ha^{-1}	Eastern Australia (N/A)	564	STEP-AWB (*n* = 28)	5.08	24.80	88.23	BRT-All BRT-GA RF-All RF-GA	Val.	0.42 0.45 0.48 0.45	7.80 7.70 7.50 7.40	- - - -	- - - -	Wang *et al.*[77] (2018)
SOC stock (L1: 0-30, L2: 30-60, L3: 60-120, L4: 120-180, L5: 0-100)	kg m^{-2}	Santa Fe River Watershed, Florida, USA (3500)	554	STEP-AWB	- (L1) 1.84 (L5)	6.26 (L1) 11.79 (L5)	- (L1) 268.91 (L5)	RK/RT (L1) RK/RT (L2) RK/RT (L3) RK/RT (L4) RK/RT (L5)	Val.	- - - - -	3.69 6.31 9.31 3.01 18.48	0.65 0.97 0.21 1.04 0.38	- - - - -	Vasques *et al.*[7] (2010)
SOC stock (0-30)	kg m^{-2}	Argentina (30,000)	18,768 (5480 soil profiles)	STEP-AWB	-	-	-	QRF	Cross-val.	*0.63*	2.94	-	-	Heuvelink *et al.*[78] (2021)
SOC stock (0-20)	t C ha^{-1}	Zhejiang province, East China (102,646)	29,927	STEP-AWBH (*n* = 23)	1.18	49.74	213.55	BoRT RF	10-fold cross-val.	0.73 0.76	11.26 10.63			Deng *et al.*[72] (2018)
SOC content (0-20)	%	Florida, USA (150,000)	850	STEP-AWBH	0.13	2.68	38.57	PLSR PLSRmod RF SBIFmod	Val.	0.71 0.77 0.68 0.78	- - - - -	1.85 2.08 1.782.15	0.45 0.51 0.44 0.53	Adi and Grunwald[66] (2019)[3]
SOC stock (0-20)	kg m^{-2}	Florida, USA (150,000)	1080	STEP-AWBH (*n* = 210; all relevant *n* = 43; minimum *n* = 4)	0.45	4.98	34.15	BaRT BoRT Cub RF	Val.	0.61 0.57 0.59 0.63	2.71 2.85 2.82 2.64	1.49 1.51 1.43 1.54	- - - -	Xiong *et al.*[37] (2014)
SOC stock (0-20)	kg m^{-2}	Florida, USA (150,000)	1014	STEP-AWBH (*n* = 327)	0.45	4.74	34.15	CaRT BaRT BoRT PLSR RF RK-RT SVM	Val.	0.57 0.70 0.68 0.64 0.72 0.63 0.66	3.42 2.48 2.56 2.82 2.39 2.99 2.62	1.32 1.81 1.75 1.59 1.88 1.51 1.71	0.94 1.30 1.26 1.14 1.35 1.08 1.23	Keskin *et al.*[69] (2019)[4]
SOC stock (L1: 0-20, L2: 20-100)	kg m^{-2}	South-eastern USA (350,000)	2564	STEP-AWB (*n* = 73)	1.10 (L1) 1.30 (L2)	3.70 (L1) 4.3 (L2)	12.60 (L1) 22.0 (L2)	RF (L1) RF (L2)	Val.	0.69 0.79	0.77 1.29	- -	2.10 1.96	Ross *et al.*[68] (2019)

SOC stock (0-20)	kg m^{-2}	France (640,679)	1,74	SE-AWB	0.25	-	26.0	BoRT (Cult model)	Val.	0.91	0.94	-	-	Martin *et al.*[70] (2011)
SOC stocks (L1: 0-5, L2: 5-15, L3: 15-30, L4: 30-60, L5: 60-100)	%	Chile (756,096)	1744	T-A	-	-	-	CNN (L1) CNN (L2) CNN (L3) CNN (L4) CNN (L5)	Val.	- - - - -	2.7 2.6 2.5 2.3 1.6	- - - - -	- - - - -	Padarian *et al.*[30] (2019)
SOC stocks (L1: 0-5, L2: 5-15, L3: 15-30, L4: 30-60, L5: 60-100, L6: 0-100)	log g/100 g	New South Wales, Australia (810,000)	5386	STEP-AWB (only results for whole models shown; local models also available)	-	-	-	Cub (L1) Cub (L2) Cub (L3) Cub (L4) Cub (L5) Cub (L6) SVR (L1) SVR (L2) SVR (L3) SVR (L4) SVR (L5) SVR (L6)	50-fold cross-val.	0.19 0.20 0.20 0.15 0.08 0.16 0.22 0.25 0.23 0.16 0.11 0.20	0.81 0.77 0.89 0.94 0.95 0.87 0.79 0.75 0.88 0.93 0.93 0.86	- - - - - - - - - - - -	- - - - - - - - - - - -	Somarathna *et al.*[53] (2016)
SOC content (L1: 0-5, L2: 5-15, L3: 15-30, L4: 30-60, L5: 60-100, L6: 100-200)	%	Australia (7.692 million)	70,803	STEP-AWB	0.001	1.73	36.32	Cub Cub-RK	Val.	-	-	-	-	Viscarra Rossel *et al.*[73] (2015)
SOC stock (0-20)	Mg ha^{-1}	USA (9.63 million)	3303	STEP-AWB	0.26	56.87	524.83	RF QRF	Val.	0.33 0.35	28.39 28.15	1.21 1.22	1.37 1.39	Cao *et al.*[75] (2019)
SOC stock (L1: 0-5, L2: 5-15, L3: 15-30, L4: 30-60, L5: 60-100)	g kg^{-1}	Canada (9.98 million)	39,366	STEP-AWB (*n* = 25 best model)	- Pred.: < 5 g kg^{-1}	-	- Pred.: > 300 g kg^{-1}	RF	5-fold cross-val.	0.72	79.8	-	-	Sothe *et al.*[76] (2022)
SOC bare topsoil	%	Europe (10.18 million)	7142	S-B, spectral data	0	1.68	43.84	BoRT	Val.	0.24	1.52	-	-	Safanelli *et al.*[117] (2020)
SOC stock	kg m^{-2}	Latin America	11,268	STEP-AWB	0	6.85	573.76	PLSR KK QRF SVM	Val. 5-fold cross-val.	Country specific r and RMSE are reported in form of graphs beyond the space of this table				Guevara *et al.*[79] (2018)
SOC content (L1: 0-5, L2: 5-15, L3: 15-30, L4: 30-60, L5: 60-100, L6: 100-200)	0/00 (g kg^{-1}) ----- SOC pred. on 250 m × 250 m global grid	Globe (510 million)	150,000 soil profiles	STEP-AWB (covariates incl. 158 remote-sensing derived properties)	-	-	-	Ensemble of 3 models (ANN, RF, BoRT)	10-fold cross-val.	0.64	32.8	-	-	Hengl *et al.*[74] (2017)
SOC content (L1: 0-5, L2: 5-15, L3: 15-30, L4: 30-60,	g kg^{-1} SOC pred. on 250 ×	Globe (510 million)	WoSIS *n* = 196,498 profiles And	STEP-AWB (400 covariates)				QRF	cross-val.		39.48			Poggio *et al.*[80] (2021)[5]

L5: 60-100, L6: 100-200)	250 (SoilGrids 2.0)	EU-LUCAS + Australia *n* = 240,000

[1]AI methods: ANN: Artificial neural network - multi layer perceptron; BaRT: bagged regression trees; BoRT: boosted regression trees; CaRT: classification and regression trees; CNN: convolutional neural networks; Cub: cubist; Cub-RK: regression kriging with cubist; GA: genetic algorithm (feature selection); KK: kernel-weighted nearest neighbors; PLSR: partial least square regression; PLSRmod: modified PLSR (with a two-step regression technique, 2Step-R that models categorical and continuous input data combining linear regressions (ridge regression - RR) and latent variable model (PLSR); RK/RT: regression kriging with regression trees; RF: random forest; SBIFmod: sparse Bayesian infinite factor regression modified with a two-step regression technique, 2Step-R that models categorical and continuous input data combining linear regressions (Bayesian linear regression) and latent variable model (sparse Bayesian infinite factor - SBIF); SVM: support vector machine; SVR: support vector regression; QRF: quantile random forest. [2]R^2: Coefficient of determination; CCC: Lin's concordance correlation coefficient[63]; RMSE: root mean square error; RPD: ratio of performance deviation[64]; RPIQ: ratio of performance to inter-quartile range[62]. [3]This study also modeled soil total (TC), recalcitrant (RC), moderately-available (MC), and hot-water extractable carbon (HC). [4]This study also modeled soil total carbon (TC), recalcitrant carbon (RC), and labile (hot-water extractable) carbon (HC). [5]This study also reported prediction interval coverage probability for soil organic carbon (SOC) for the six modeled soil layers.

No specific AI method stood out among reported soil carbon studies as superior. Random Forest was one prominent ML method applied in numerous SOC assessments[37,66,68,69,71,72,74-77] though the example studies assembled in Table 1 are not exhaustive. Deep learning algorithms are rarely used in soil carbon modeling (e.g., SOC assessment in Chile by Padarian *et al.*[30], 2019). More recently, the AI method QRF has gained interest to model SOC due to its ability to assess confidence intervals of estimates. For example, QRF was employed to model SOC in Argentina[78], Latin America[79], United States[75], and globally[80]. In studies that compared SOC models derived from multiple AI methods differences among AI methods were rather subtle[69].

Noteworthy, error metrics and uncertainty assessments were rarely provided by previous regionalized and global carbon assessments demonstrating the power of AI modeling. For example, the global potential of SOC sequestration through the adoption of conversation management practices and restorative land use was estimated at 0.9 ± 0.3 Pg C yr^{-1}, which was considered to offset one-fourth to one-third of the annual increase in atmospheric CO_2 estimated at 3.3 Pg C yr^{-1}[81]. Global SOC storage was assessed using the Harmonized World Soil Database by Köchy *et al.*[82] (2014) and a transfer function approach was used to map global soil carbon stock by Minasny *et al.*[19] (2017). The global soil carbon map (GSOCMap) on a 1 km × 1 km grid covering the topsoil (0-30 cm) by the FAO Global Soil Partnership is a joint effort of nations around the globe. The global carbon budget provided by Le Quéré *et al.*[83] (2015) used a budgeting approach to assess different carbon pools and fluxes whereby soil carbon was lumped into the category residual terrestrial carbon sink due to limited reliable data. Noteworthy, there was limited use of AI in these global SOC assessments. Recently, the achievable SOC sequestration in croplands and grasslands around the globe was estimated by Batjes[84] (2019) with two different approaches. The first one based on literature estimates of SOC gains by bioclimatic zones (M1) and the other assumed an annual C increase of 3 to 5 promille with respect to current SOC mass. According to M1, achievable gains ranged from 0.05-0.12 Pg C yr^{-1} to 0.14-0.37 Pg C yr^{-1}, with a technological potential of 0.32-0.86 Pg C yr^{-1}, while for M2 gains were 0.07-0.12 Pg C yr^{-1}, 0.21-0.35 Pg C yr^{-1}, and 0.60-1.01 Pg C yr^{-1} based on four different management scenarios. The provision of soil carbon values and/or SOC maps without explicit error and uncertainty analysis leaves major ambiguities due to lack in confidence in reported soil carbon values. AI and rigorous uncertainty assessment avoids such pitfalls.

AI-based soil respiration modeling

Soil respiration (R_s) provides one of the largest global fluxes of carbon dioxide (CO_2) to the atmosphere. Global R_s indicates the level of microbial activity and plays a major role in the global carbon cycle. It was conceptualized that rising global temperatures are expected to lead to substantial higher decomposition rates of soil carbon, and thus, CO_2 release from soils. However, despite its importance, the response of soil carbon to warming is still one of the great uncertainties in global carbon cycling[85,86]. Some studies found that R_s is mainly controlled by a range of biotic and abiotic factors, specifically temperature and other climatic factors[87-89], while other studies found that temperature is not the primary driver for the response of R_s to global warming. For example, Haaf *et al.*[85] (2021) found that global R_s is mainly controlled by interacting soil properties and secondarily by vegetation traits and plant growth conditions. Haaf *et al.*[85] (2021) pointed out that mechanistic controls of microbial soil R_s in response to global climate warming are well understood at the experimental laboratory and plot scale; however, soil properties are "hidden" from remote sensing and challenging to be mapped accurately at a spatial scale at which microbial soil properties and associated ecosystem processes vary in nature. In a global AI analysis, Huang *et al.*[90] (2020) found that land cover change, not climatic factors, played the most important role in regulating R_s changes specifically in temperate and boreal regions. AI modeling of site-specific R_s data coupled to gridded environmental datasets has afforded to discern the effects of climatic, biotic, edaphic, and other variables on R_s, heterotrophic respiration (R_h), and autotrophic respiration (R_a).

One of the first global soil respiration studies found that R_s increased by 0.1 Pg C yr^{-1} (1989 to 2008) with global R_s integrated over the Earth's surface amounting to 98 ± 12 Pg C implying a global R_s response to air temperature (Q_{10}) of 1.5[91]. Similar quantifications found that global R_s rates derived from flux measurements responded to the increase in air temperature at the rate of 3.3 Pg C yr^{-1} °C^{-1}, and Q_{10} of 1.4 for the period 1965 to 2012[92] and R_s of 94.3 ± 17.9 Pg C yr^{-1}[93]. These global R_s assessments used simple transfer regression functions approaches, while more current regional and global R_s assessments have incorporated AI. Recently, the AI algorithm RF was compared to ten different terrestrial ecosystem simulation models to compute global R_s with the former AI model outperforming all simulation models in a performance analysis using R_s measurements[89]. In this global study, the RF model showed excellent performance with R^2 of 0.89 for R_s and 0.86 for HR with 85.5 Pg C yr^{-1} for R_s and 50.3 Pg C yr^{-1} for R_h. The average global R_a (i.e., the difference between R_s and R_h) was 35.2 Pg C yr^{-1} for the RF model. In contrast, the estimated global R_s and R_h by the ten ecosystem models ranged from 61.4 to 91.7 Pg C yr^{-1} and 39.8 to 61.7 Pg C yr^{-1}, respectively, which indicates the wide variability in results derived from process-based simulation models. Findings suggest that mechanistic modeling of soil R_s metrics showed higher uncertainty than the AI model. Notably, the contribution of R_a to R_s highly varied among the ecosystem models (between 18% to 48%), which differed to the estimate computed by RF (41%)[89].

In another global study, Warner *et al.*[94] (2019) used plot-derived R_s measurements (n = 2657) and the AI-ML method QRF to make R_s predictions onto a 1 km × 1 km grid across the globe. Environmental predictor variables [mean annual temperature (MAT), mean annual precipitation (MAP), mean annual MODIS EVI, and mean precipitation from November through January] yielded a QRF prediction model with a global area-weighted mean annual R_s of 592.2 ± 368.9 g C m^{-2} yr^{-1} and a global sum of 87.9 Pg C yr^{-1}. The R^2, RMSE, and MAE were 0.63, 305.2 g C m^{-2} yr^{-1}, and 141.0 g C m^{-2} yr^{-1}, respectively. Recently, QRF was also used to model global R_s at a 1 km × 1 km spatial grid using large experimental datasets (small set n = 5173 and large set n = 10,366)[95]. In this study, the smaller dataset obtained a global R_s sum of 88.6 Pg C yr^{-1} (MAE = 29.9; Std. = 57.9 Pg C yr^{-1}), whereas the model with the larger R_s dataset yielded 96.5 Pg C yr^{-1} (MAE = 30.2; Std. = 73.4 Pg C yr^{-1}). The inclusion of new data from underrepresented regions (e.g., Asia, Africa, South America) to build the larger dataset resulted in overall higher model uncertainty. These are surprising findings

because commonly AI models tend to improve model performance when using larger datasets, though in some instances increasing the sample size may also increase data variability that may negatively affect model performance. The global R_h from the small dataset was 49.9-50.2 (mean 50.1) Pg C yr^{-1} and from the larger dataset it was 53.3-53.5 (mean 53.4) Pg C yr^{-1}. Other global R_s modeling involved the application of AI-DL methods (ANN) which computed a global average R_s of 93.3 ± 6.1 Pg C yr^{-1} from 1960 to 2012 and an increasing trend in average global annual R_s of 0.04 Pg C yr^{-1}. This global R_s model used climatic (MAP and MAP) and biome type as predictor variables resulting in an R^2 of 0.60.

The spatial and temporal variations in global R_s and their relationship with climate and land cover was assessed using a global dataset of R_s measurements (2000-2014), satellite data, and various AI algorithms (RF, SVR, and ANN) and a traditional method (multivariate nonlinear regression, MNLR). The selected models explained 62% to 84% of the interannual and intersite variabilities in annual R_s with an RMSE ranging from 107 to 413 g C m^{-2} yr^{-1}[90]. In the 10 different global biomes the MNLR model (R^2 between 0.20-0.55; RMSE between 140-519 g C m^{-2} yr^{-1}) was outperformed by all of the AI models estimating R_s. The model performance of the RF was best in 6 biomes (R^2 between 0.47-0.68; RMSE between 148-429 g C m^{-2} yr^{-1}), followed by SVM in 4 biomes (R^2 between 0.41-0.69; RMSE between 132-438 g C m^{-2} yr^{-1}). The ANN model estimating R_s showed moderate performance (R^2 between 0.35-0.62; RMSE between 158-446 g C m^{-2} yr^{-1}). Boreal, temperate, and tropical regions contributed 15%, 24%, and 61%, respectively, to the total mean annual global R_s. Land cover was the primary explanatory variable for global R_s. The areas with significant changes in short vegetation cover (i.e., all vegetation shorter than 5 m in height) showed more frequent changes in R_s than in areas with significant climate change.

A data-driven AI approach (RF) was also employed to assess the effects of climatic, edaphic and productivity on R_h with n = 455 at global scale[96]. In this study global R_h was 46.8 Pg C yr^{-2} (1985-2013) with a significant increasing trend of 0.03 Pg C yr^{-2}. In this study, water availability dominated R_h inter-annual variability. Water availability dominated in extra-tropical forest and semi-arid regions, while temperature strongly controlled R_h in tropical forests.

There are numerous factors that enabled the shift toward AI-R_s (and R_h and R_a) global modeling. First, the assembly of large databases that harmonized thousands of soil R_s plot-scale data enabling global AI modeling[88,97]. Although the presented R_s-AI studies were derived at global scale, the same AI approaches are also applicable to investigate R_s at regional scales. Site-specific R_s data coupled to geospatial environmental grids have allowed to go beyond descriptive assessment of global R_s change. AI models facilitated to upscale R_s onto a global grid with commonly used spatial resolutions of 1 km × 1 km. Global AI R_s models outperformed more traditional methods (multivariate regression), though there was still a substantial portion of unexplained variability in models. This points to data limitations rather than AI modeling limitations given the expansive cloud computing and supercomputer capabilities. One major data limitation to all global studies is the unbalanced distribution of soil R_s measurement sites around the globe which are concentrated in North America and Europe, but sparser in other regions. Jian *et al.*[98] (2018) cautioned that recent global R_s models showed a wide range from 68 to 98 Pg C yr^{-1}, which suggests considerable uncertainty impacting global carbon accounting. In Jian *et al.*[98]'s (2018) study a sensitivity analysis using RF was performed that varied timescales (daily, monthly, and annual) of R_s and climate data to predict global R_s which ranged from 66.62-100.72 Pg (1961-2014). Using monthly R_s data rather than annual data decreased global R_s by 7.43-9.46 Pg. In contrast, global R_s calculated from daily R_s data was only 1.83 Pg lower than the R_s from monthly data. Using mean annual precipitation and temperature data instead of monthly data caused +4.84 and -4.36 Pg C differences, respectively. These results suggest that temporal slicing of R_s and climatic data impact AI estimates of global R_s, and thus the global carbon budget.

THE POWER, POTENTIALS, AND PERILS OF AI-BASED SOIL CARBON MODELING

There is no doubt that AI modeling provides advanced capabilities to predict SOC stocks and R_s. Though these AI models are still data limited in explaining the spatial variability of soil carbon storage within landscapes. Specifically, SOC measurements used at large region and global scale are derived from legacy databases with a smaller amount of data that represent current field conditions. The temporal mismatch between up-to-date environmental covariates and legacy SOC data may be another limiting factor. Proximal soil sensing (VNIR and MIR spectroscopy) has been pivotal to counter these trends and estimate SOC and other soil properties rapidly, cost-effectively, densely, and accurately through the application of AI. For example, SOC was estimated by AI from proximal sensing data at global scale by Viscarra Rossel *et al.*[99] (2016), in Florida by Knox and Grunwald[100] (2018), in regions in India by Clingensmith *et al.*[101] (2019), in Brazil by Moura-Bueno *et al.*[102] (2021), and in China by Shi *et al.*[103] (2014). The incorporation of VNIR and MIR spectral data along with remote sensing data into AI models that upscale SOC storage to large regions is promising[67].

Soil respiration observations have been integrated into global open-access databases[87,97] to be shared and used by the scientific community. Regional R_s data can be spiked into these global databases which facilitates global research on AI-R_s. Soil respiration data represent carbon fluxes (i.e., temporal state of an ecosystem), while SOC storage infers on the spatially-explicit state of an ecosystem. AI models to predict SOC sequestration rates are still in its infancy due to data availability. One example, to model SCseq using CART in no-tillage systems compared to conventional tillage systems at global scale was provided by Sun *et al.*[16] (2020). The open-access approach of global R_s data repositories differs from SOC data. The latter are limited by the access to data with due to different purpose: (1) regional AI-SOC research projects with up-to-date data that represent field conditions; (2) some national SOC data that have restricted access while others are public (e.g., U.S.); and (3) global public SOC data - for example, the World Soil Information Service (WoSIS) database - which includes more legacy data than up-to-date SOC data. In summary, some limitations for AI soil carbon modeling are due to limited data sharing and currency of data. Though the contribution of community SOC data into larger open-access global databases rests on fair data sharing policies that acknowledges the labor and costs involved in field and laboratory operations. Investments to collect new soil samples analyzed for SOC (topsoil and subsoil), consistent SOC monitoring at benchmark sites around the globe, and boosting of R_s measurements would greatly benefit future AI soil carbon modeling.

Furthermore, ethical concerns entail the amplified focus and reliance on AI technologies and machine-generated model outputs that lack knowledge discovery and human interpretation of soil carbon dynamics across large and complex soil-ecosystems[33]. Wadoux *et al.*[104] (2020) presented results that compared RF models created with real SOC observations and one from pseudo ("false") variables for the same region. These AI models produced comparable results to predict SOC which raises major concerns about the possibility of AI generated "digital fake" versions of soil carbon storage. These concerns about AI models were echoed by Liao[105] (2020) who pointed out that AI methods are prone to erratic behavior of model outputs due to outliers or misclassified pixels and are sensitive to pseudo ("false") variables. As the collection of geospatial environmental datasets, specifically sensor-derived data, is steadily increasing the risk to incorporate spurious predictor variables into soil prediction models also increases[33]. Data-driven AI modeling of soil carbon dynamics is prone to identify relations between massive and diverse datasets of input variables (environmental covariates) and outputs (SOC stock, R_s, or others) that may statistically exist, but from a physical or biogeochemical knowledge perspective make less sense.

Protection against such pitfalls is the application feature selection processing methods pre-AI modeling. Commonly used pre-processing methods are Recursive Feature Elimination (RFE) analysis to select the best performing subset of covariates which was described by Guyon *et al.*[106] (2002). The RFE procedure starts with the maximum number of covariates and iteratively removes the weakest explanatory variable until a specified number of covariates is reached. Heuvelink *et al.*[78] (2021) used RFE to identify covariates to model SOC stocks in Argentina using the QRF AI algorithm and Poggio *et al.*[80] (2021) used RFE before running the QRF AI algorithm to model global SOC. The Boruta algorithm, often used in combination with RF, is another pre-processing method to strategically filter out the most important environmental covariates that relate most strongly to a target output[107]. Boruta was applied successfully to build parsimonious RF-AI SOC prediction models that substantially reduced large environmental covariate sets[37,69]. Xiong *et al.*[37] (2014) compared various pre-processing algorithms that discerned all-relevant variables (i.e., strong and weakly relevant variables selected with Boruta and RF), minimal-optimal variables (four optimization algorithms were tested: greedy forward, greedy backward, hill climbing, and simulated annealing), and irrelevant environmental covariates to model SOC stock using four different AI methods (BaRT, BoRT, RF, and Cubist) in Florida, USA. The initial environmental covariate set comprised 210 variables, while the best performing parsimonious model identified with the all-relevant and minimal-optimal feature selection comprised just four covariates to predict SOC stock[37]. This holistic AI environmental modeling framework was based on the consistent feature selections in ML approach developed earlier by Nilson *et al.*[108] (2007). The advantage of automated feature selection compared to expert-based selection of covariates is that human bias is reduced that may, even unintentionally, impact SOC modeling and upscaling of results to region or global scale.

Another powerful feature selection methods is sparse Least Absolute Shrinkage and Selection Operator (LASSO)[109]. For example, LASSO as well as Boruta feature selections were employed along with AI-ML and AI-DL algorithms to model SOC in two contrasting climatic regions[110]. Wang *et al.*[77] (2018) found that the genetic algorithm outperformed stepwise multivariate regression in strategically selecting predictor variables before applying RF and BoRT to model SOC stocks in rangeland in Eastern Australia. While the application of feature selections in AI-SOC modeling is prominent (see studies in Table 1), it seems relatively rare in global AI-R_s modeling studies. Interestingly, in global AI-R_s studies knowledge discovery is emphasized over technical information of AI modeling that often is only provided in small print in appendices and supplementary documents of publications. Instead, separate pre- or post-hoc analyses that complement AI modeling are commonly found in the global R_s literature[111].

The dichotomy between data-driven and knowledge-driven soil modeling was discussed in detail by Wadoux *et al.*[104] (2020). Authors cautioned about knowledge discovery purely from ML and pattern recognition processes. It was suggested that pedologically relevant environmental covariates should be selected through feature selection pre-processing. In similar vein, McBratney *et al.*[28] (2019) raised concerns around over-parameterization and the generation of nonsensical soil predictions from AI models. In my view, an important vision going forward with AI soil carbon modeling is to keep balance between (1) data-driven feature selection and ML and DL modeling; and (2) knowledge-driven approaches pre-AI modeling and post-interpretation. Scientific interpretation enhances legitimacy and confidence in AI-generated digital soil C output. Ideally, an integral scientific approach involves consultation of multiple other sources (environmental datasets, literature, expert-knowledge) and comparative analysis derived from other methods rooted in a modeling paradigm different from AI (e.g., process-based simulation modeling, geostatistics, hybrid stochastic-deterministic methods, Bayesian methods, structural equation modeling, participatory action research). Ensemble modeling to aggregate soil carbon output from various, ideally contrasting model paradigms among them AI, may lower the risks of spurious AI model output. Meta-

modeling, an approach rooted in integral ecology, was envisioned as a viable framework for integration of multiple models and data to address soil security issues, among them soil carbon sequestration[112]. An integrative vision for soil carbon assessments would avoid the inflated hype about AI in carbon sciences. Such integrative strategy lowers the risk to "blindly" belief machine-generated soil carbon assessments; even validation of AI-generated results cannot fully inoculate from potential spurious modeling results that may be replicated in training and validation modes. Honoring the diversity of modeling approaches that provide partial knowledge of soil carbon dynamics rather than idealizing AI as superior to all other methods will further enhance scientific understanding of complex soil-ecosystems and carbon dynamics. It may also help to form resilient liaisons and partnerships among AI specialists and soil and environmental scientists.

The shift from simple ML rooted in pattern recognition toward more complex DL models with multiple layers of nodes, processing strategies (e.g., convolution and pooling), and fitting strategies (e.g., latent factors or weights) makes these kinds of models (see Figures 2-5) more abstract losing more-and-more physical and pedological meaning. Theoretically, these fitting and learning strategies in ANN model variants if put to the extreme could achieve an ideal model fit (R^2 of 1), which has been approximated already in soil carbon modeling applications. For example, CNN and Cubist were used to model various soil properties, among them SOC, using VNIR and MIR spectral soil data using a large dataset (n = 14,594) from the U.S.[113]. In this study, the two-channel 1D CNN model was best performing with R^2 between 0.95 and 0.98 for six different soil properties, the R^2 was 0.98 for both SOC and soil total carbon, and the RPIQ was 2.27 (SOC) and 3.01 (soil total carbon). These results are "near-perfect" though one may wonder about the many hyperparameters and processing layers in the CNN for tuning to achieve such superb model performance [Figure 5]. The many hyperparameters, latent factors, and fitting weights in AI models make sense to the machine, but are less meaningful for interpretation by human users or carbon scientists to infer on carbon cycle processes, soil functions, or ecosystem services. What pedological or biophysical insights in regard to SOC or ecosystem processes were derived in Ng *et al.*[113] (2019) research study or similar AI-DL soil carbon models? The extraordinary capabilities of AI-DL algorithms to fit inputs and outputs have been hailed black-boxes and AI-ML algorithms gray boxes, respectively; in essence, AI models lack transparency[105]. Black-boxes or gray-boxes mean, for example, that SOC storage or the ecosystem process of SCseq are encoded in AI-ANN models in form of multiple nodes, layers, and weighing factors replacing human understanding and striving for meaning-making about the soil-environment into machine code.

From a philosophical perspective, the question is whether the physical environment or a simulated, virtual environment (digital worlds) is more real to us. Chalmers[114] (2022) in his book *Reality+* discerned between virtual simulated worlds and those we perceive as real and suggested that we can live meaningful lives in virtual reality. Applying Chalmer's vision to carbon science this suggests that we would be able to live meaningful lives in machine generated worlds in which a soil carbon map or model is as real and satisfying as a soil in nature. Interestingly, in such a virtual/AI soil carbon world human knowledge and understanding of soil-environmental relations, mechanisms, ecosystem processes, carbon fluxes and cycling, and global climate change become irrelevant.

Given the rapid expansion of AI into carbon science, as well as many other sciences, poses urgency to think about ethical implications implicated in AI[105,115]. Reality+ confronts us with the question what is "real and meaningful to us" - an observable soil in nature that we can touch, sense, and use (phenomenology), laboratory measurements of the soil carbon content (empiricism), proximal or remote sensors and AI providing inference on soil carbon, a digital image/map of soil and its carbon storage computed by AI (representation), or simulated worlds (simulacra) created with advanced AI and visualization techniques. These simulacra replace "environmental reality" with its representation according to Baudrillard[116] (1994).

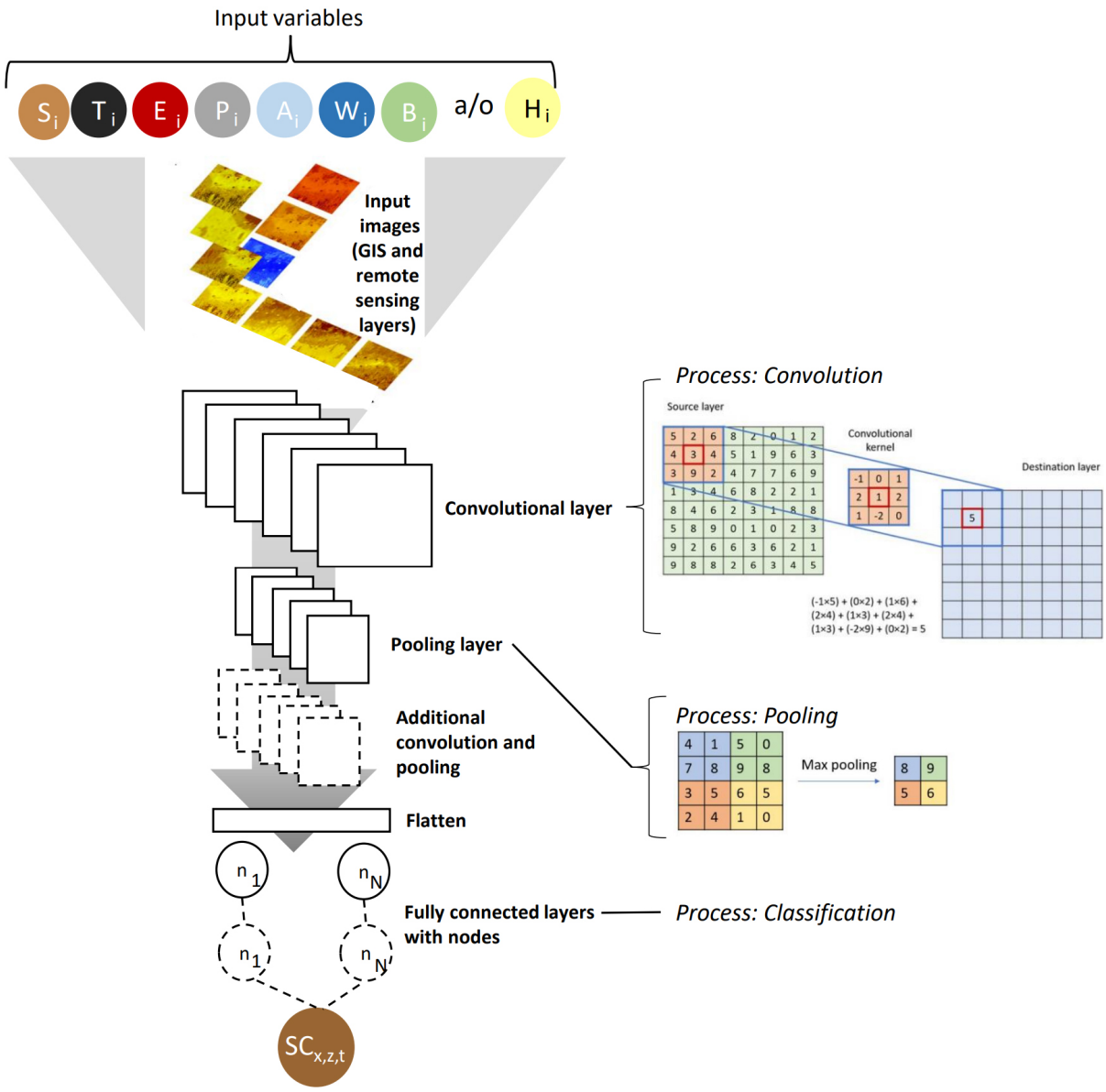

Figure 5. AI model predicting soil carbon (SC) from environmental covariates. Idealized model representation of a convolutional neural network (CNN).

He philosophized that society had become saturated with simulacra and that people live in a hyperreality in which meaninglessness prevails. While Baudrillard[116]'s (1994) vision was somewhat dystopian, Chalmer[114]'s (2022) Reality+ looks more optimistic. Whether the expansion of AI-DL and AI-ML soil carbon modeling is perceived as frustrating and frightening because only the machine knows leaving one confused, helpless, and meaningless or whether we get excited and enchanted by the beauty of machine-generated soil carbon data, maps, and models that we trust will have a profound impact on carbon science and how it is applied in carbon policies, carbon crediting, and carbon management. The risks involved are that AI-generated soil carbon hyperreality is prone to human manipulation (i.e., how the model is tuned and fitted) and misuse.

One key question is whether we are applying AI in data-driven or knowledge-driven ways to advance soil carbon science. The potentials and perils of AI in carbon science need to be carefully weighted to avoid pitfalls, and perhaps compute (surprising), spurious digital soil carbon predictions. The power of AI is the possibility of more accurate and precise soil carbon models that only machine algorithms can create. In the latter lies the profound potential of AI-ML and AI-DL to transform carbon science and modeling. Enhanced dialogue and awareness of AI model limitations may help to better understand soil carbon evolution and its ecosystem processes.

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Carbon Footprints

Perspective

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Perspectives on carbon footprint of agricultural land-use in Brazil

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Abstract

Brazil is one of the main producers in the agricultural and forestry sector worldwide, with production systems based on high consumption of inputs that contribute to high levels of greenhouse gas (GHG) emissions. This paper presents an analysis of the scenario of national GHG emissions and carbon footprints in the major production systems of agriculture, including livestock production and forestry, and the potential for soil carbon storage as a mitigation strategy under these systems. The main sources of national GHG emissions are beef cattle due to enteric fermentation and the management of agricultural soils through the use of nitrogen fertilizers. The increasing adoption of low-carbon agriculture has led to a reduction in the carbon footprint through no-till technologies, agrosilvopastoral systems, N_2 fixation, and tree plantations. These technologies deserve to be increasingly disseminated to generate economic opportunities leading to financial gains from the commercialization of carbon credits and payment for environmental services.

Keywords: GHG emissions, low-carbon agriculture, land-use systems, sustainable intensification

INTRODUCTION

Agriculture is practiced throughout the national territory of Brazil, covering six different biomes (Amazon, Cerrado, Atlantic Forest, Caatinga, Pantanal, and Pampa) that present variations in climate, soil, vegetation, water regime, relief, and specific demands in the environmental, social, and economic sectors, in addition to presenting different types of agricultural production systems. This complexity represents a major challenge in terms of meeting the goals of food security, increased productivity, and sustainable production standards. Since the implementation of the green revolution in Brazil in the 1960s, the agricultural and forestry sectors have undergone major changes with the ultimate objective of obtaining the highest yields. The production process was intensified with the large-scale use of machinery and other inputs for maximizing the production of crops and commodities for the foreign market. Thus, monocultures and agro-industry were intensified as viable and very profitable economic activities.

This production model based on high consumption of inputs causes additional greenhouse gas (GHG) emissions that contribute to global climate change with soil degradation (compaction, erosion, and reductions of organic matter levels and soil fertility) and reduced biodiversity, among other losses[1]. Total gross GHG emissions reached 2.16 billion tons of CO_2 equivalent ($GtCO_2eq$) in Brazil in 2020. Land use changes were the most responsible for GHG emissions due to deforestation and burning of native vegetation for agricultural use, mining activities, and urban expansion. Other major sectors include agriculture, energy sector, industrial processes, and waste management[1] [Figure 1]. Thus, most national emissions are directly or indirectly linked to agricultural production and land-use change. The present paper describes the national GHG emissions, the carbon footprints in some production systems, and the potential for soil carbon storage as a mitigation strategy in Brazil. The use of low-carbon agriculture and a reflection on the need for paradigm shifts towards sustainable development are also emphasized.

The agricultural sector

The strategic relevance of the agricultural sector for Brazil lies in the fact that it aggregates the various production chains of agriculture (crops and livestock) and tree plantations, which together constitute the country's agribusiness sector. This sector employed approximately 19 million people in 2021, including workers in both the countryside and companies linked to the agribusiness chain. Of this total, 11.5 million workers are linked to family farming, representing most of the jobs created in the countryside and the majority of Brazilian agricultural properties[2]. This agribusiness model contributed 26.6% of the national gross domestic product (GDP) in 2020. The country's GDP totaled BRL (Brazilian Real, R$) 7.45 trillion (R$1 = approximately USD 0.20, early 2022), and the agricultural sector's GDP reached almost BRL 2 trillion (70% from the agricultural sector and 30% from livestock)[2], while the forestry sector contributed around R$100 billion[3]. The performance of agricultural production was due to the high commodity prices in the international market, mainly grains, coffee (*Coffea arabica*), meat, and eucalyptus (*Eucalyptus* sp.). However, revenue growth was limited by rising production costs since most of the inputs (fertilizers, pesticides, herbicides, *etc.*) were imported. These, as well as the cost of fossil fuels (diesel and gasoline), are subject to the uncertainties of international market prices.

Brazil has been a major producer and exporter of several commodities including soybeans (*Glycine max*), maize (*Zea mays*), beans (*Phaseolus vulgaris*), sugarcane (*Saccharum officinarum*), coffee, cocoa (*Theobroma cacao*), and livestock for the past several decades[4,5]. The estimated total grain production for the 2021/2022 harvest was 291.1 million tons from 72 million hectares (8.5% of the total area of the national territory). This

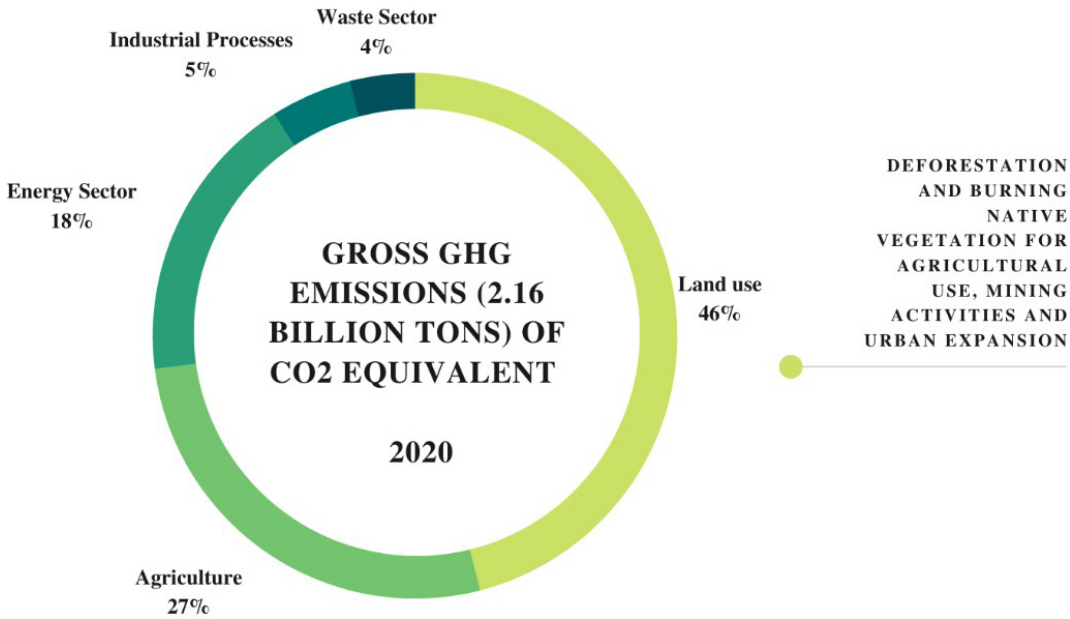

Figure 1. Total gross GHG emissions reached 2.16 billion tons of CO_2 equivalent (G_tCO_{2eq}) in Brazil in 2020.

corresponded to a 15% increase compared to the 2020/2021 harvest, with an 11% increase in productivity, for an increase of only 3.7% in planted area. Most of the total planted areas of grains are used for producing soybeans (56%) and maize (29.1%), with beans on about 4% of the area [Table 1]. The area under sugarcane for the 2021/2022 harvest corresponded to approximately 1% of the total area of the national territory with a production of 568.4 million tons, while the coffee plantation area was 0.2% and cocoa 0.07%, producing 47.7 million bags of coffee (1 bag = 60 kg of coffee) and 259,310 tons of dry cocoa beans [Table 1]. The size of the area occupied by the main vegetable crops in Brazil represents 2.5% of the area occupied by soybeans, producing 20.8% of the volume and 16.4% of the revenue. Tomatoes (*Solanum lycopersicum*), onions (*Allium cepa*), carrots (*Daucus carota*), potatoes (*Solanum tuberosum*), garlic (*Allium sativum*), sweet potatoes (*Ipomoea batatas*), melons (*Cucumis melo*), and watermelon (*Citrullus lanatus*) are the main vegetables grown in Brazil. Beef cattle herds totaled approximately 218.2 million head reared on 160 million hectares of pastures[6].

The Brazilian forestry sector has been characterized as a major international player in the industrial tree plantation sector since 2000. Since then, it has been characterized by the expansion of planted areas and the consolidation of the sector's technological development. Forest products are the third largest in terms of national agribusiness exports value, below soybean and meat production. Tree plantations in Brazil totaled about 9 million hectares in 2020, of which 7.5 million hectares were planted with eucalyptus, 1.7 million hectares with pine, and 0.4 million with other species, including rubber (*Hevea brasiliensis*), acacia (*Acacia sp.*), teak (*Tectona grandis*), and paricá (*Schizolobium amazonicum*)[3]. Consumption for industrial uses from tree plantations totaled 216.6 million m^3 of wood in 2020, with eucalyptus plantations representing 75% of this total. The paper and cellulose sector stood out as the main consumer (41% of the total), followed by industrial firewood (25%), wood industry (15.5%), charcoal sector (11%), reconstituted panels (6.5%), treated wood (0.6%), and others (1.0%)[3].

The productivity increases of most commodities have been attributed to the increasing use of agrochemicals[7,8]. For example, fertilizer consumption increases every year (between 30 and 35 million tons

Table 1. Planted area, productivity, and estimated production of some commodities in Brazil for the 2021/2022 harvest

Crop	Area (ha)	Productivity (kg/ha)	Production (in 1000 t)
Soybean[1]	40,351.7	3539	142,789.9
Maize[1]	20,939.3	5596	117,181.5
Beans[1]	2907.9	1079	3136.6
Sugarcane[1]	8264.4	68,780	568,430.2
Coffee[2]	1,808,462	1584	2,862,960
Cocoa[3]	581,884	446	259,310

[1]Estimated area in 1000 ha (source: CONAB[4]). [2]Coffee productivity in 26.4 bags per hectare (1 bag = 60 kg). Coffee production in 47,716 million bags (source: CONAB[4]). [3]Cocoa production in tons in the year 2019 (259,310 t = 259,310,000 kg) (source: Gama-Rodrigues *et al.*[5]).

during the period 2013-2020) in view of the advancement of agriculture in the country and the need to increase productivity in mostly low fertility and very acidic soils. While Brazil's fertilizers supply the domestic agricultural sector, the demand is much greater than the production capacity of the national industry[7]. Other inputs (pesticides, herbicides, *etc.*) follow the same trend as fertilizers, as their consumption has increased by approximately 380% between 2000 and 2019. The inappropriate use of these inputs compromises the growth of the Brazilian agricultural and forestry sector in terms of the quality of the environment and the product generated.

Greenhouse gas emissions

Emissions in the agricultural sector are mainly from the digestion of ruminant animals, which emit methane (enteric fermentation), and the management of waste from these animals. GHG emissions also derive from the cultivation of irrigated rice, burning of agricultural residues, sugarcane and cotton cultivation, and those originated from the way agricultural soils are managed, considering the increase in nitrogen through the use of agricultural inputs and operations[1].

Agricultural sector emissions have increased by 47.8% since 1990, mainly due to farmland management (+109%) by the use of synthetic and organic fertilizers, the management of animal waste (+58.6%), and due to increases in the population of cattle (enteric fermentation, +31.9%). There was a small increase in the contribution of irrigated rice cultivation (+11.8%); however, there was a drastic reduction in burning agricultural residues (-80.4%) [Table 2]. Enteric fermentation (methane) was responsible for 64.6% of gross GHG emissions in 2020, followed by agricultural soil management (28.8%), manure management (4.7%), rice cultivation (1.8%), and burning of agricultural residues (0.1%) [Table 2]. Agricultural soil management is the main N_2O emitter into the atmosphere, accounting for 85% of the country's total due to waste deposition in the soil and application of nitrogen fertilizers, with a direct influence on increasing the productivity of national livestock and agriculture production[9]. Additionally, direct manure deposition on the soil by animals in pastures contributes to 34% of emissions from managed pasture soils, followed by the application of organic fertilizers (30%), synthetic fertilizers (24%), agricultural residues incorporated into the soil (9%), and management of organic soils (3%)[10].

Several studies have been developed in the last 20 years to measure the potential for GHG emissions in sugarcane production[11], irrigated rice[12], maize[13], soybeans[14], beans[15], integrated crop-livestock system[16], oranges[17], beef cattle[18], agroforestry systems[19], eucalyptus[20], and other land uses[21]. All of these case studies evaluated different soil management practices, with the emphasis on applying different sources of synthetic nitrogen fertilizers and the use of animal waste, seeking to develop specific methods for measuring GHG emissions suited to the environmental conditions of each production system [Table 2].

Table 2. Estimate of GHG emissions from agriculture in Brazil (TCO_2eq - GWP AR5)

Emission factor[1]	1990	2000	2010	2020
Enteric fermentation	282,683,055 (72.4)	312,364,176 (71.3)	368,496,315 (69)	372,973,344 (64.6)
Rice cultivation	9,272,835 (2.4)	10,311,099 (2.4)	10,793,789 (2)	10,369,554 (1.8)
Management of animal waste	17,022,803 (4.4)	18,201,021 (4.2)	22,843,859 (4.3)	26,996,464 (4.7)
Burning of agricultural residues	1,886,873 (0.5)	1,794,206 (0.4)	2,055,441 (0.4)	369,800 (0.1)
Managed soils*	79,587,469 (20.3)	95,386,419 (21.7)	129,884,998 (24.3)	166,313,837 (28.8)
Total	390,453,035	438,056,921	534,074,403	577,022,998

[1]Adapted from Potenza *et al.*[1]; the numbers in parentheses represent the annual percentage of each emission factor; *input addition - particularly nitrogen fertilizers.

Carbon footprint

As a result of human activities, significant increases in GHG emissions around the world have led to the development of the concept of the carbon footprint (CF). Carbon footprint corresponds to the amount of GHG (expressed in CO_2eq) emitted for the production of a commodity unit during a given period, and CF makes it possible to establish changes in production systems to meet the goals of low-carbon agriculture[22]. The important thing for measuring the CF of a crop or product is to consider all activities and inputs at various stages of the production chain: inputs of fertilizers, herbicides, pesticides, and others (inherent in the specifics of different production systems); the use of fuel and energy in field operations; irrigation and transport of inputs to the farm; and harvested products and co-products from the farm to their processing or storage locations. This assessment also takes into account production data, waste management, and soil characteristics, as well as C stock and other management decisions (type of crop, cover crops, and land conversion)[23].

Few studies have evaluated the CF in Brazil, mostly restricted to case studies at the farm scale. Several methodologies have been used in these studies seeking to meet the specificities of each evaluated production system. As a result, different GHG emission factors were considered in the CF calculations, which make it difficult to obtain a national standard for the agricultural sector's production chains.

DISCUSSION

Strategies and challenges for low-carbon agriculture

The Brazilian government created the Sectorial Plan for Mitigation and Adaptation to Climate Change in 2009, being called the Low-Carbon Agriculture (LCA) Plan [*Plano Agricultura de Baixa Emissão de Carbono* (*ABC*)], as part of the commitment to reduce GHG emissions, assumed at the 15th Conference of the Parties in Copenhagen. The LCA Plan supports 5 million rural households across the country and aims to ensure the continuous and sustained improvement of management practices, which reduce GHG emissions and additionally increase the fixation of atmospheric CO_2 in the plant-soil system of the various sectors of Brazilian agriculture. Examples of sustainable technologies and systems for agricultural production include no-tillage (NT), agrosilvopastoral systems, recovery of degraded pastures, biological nitrogen fixation (BNF), and tree plantations[24,25].

The expansion of the LCA Plan promoted an increase in the area of integrated production systems from 5.5 to 11.5 million hectares from 2010 to 2015, of which 83% with agropastoral systems, 9% with agrosilvopastoral, and 7% with silvopastoral systems[26]; expansion of the NT area by approximately 36 million hectares in 2018[27]; and a 166% increase in areas with BNF in the period from 2010 to 2020, totaling 14.6 million hectares. Among the partially met targets is the expansion of 1.9 million hectares of tree plantations during the period from 2010 to 2020, corresponding to 60%-76% of the target[1]; an increase of

13.2 million hectares in the recovery of degraded pastures, the target being 15 million hectares; and partial compliance of only 39% expansion in the use of technologies for treating animal waste[1].

Today, the LCA in Brazil is a reality with favorable results on C sequestration and reduction of CF in different land use systems. This has been achieved through strategies focused on sustainable development and the conservation of natural resources. Such strategies have promoted the reduction of GHG emissions by 6.1 million (TCO_2eq - GWP AR5) through tree plantations, 50.6 million (TCO_2eq - GWP AR5) through an integrated crop-livestock-forest system, 53.6 million (TCO_2eq - GWP AR5) through no-till practices, and 105 million (TCO_2eq - GWP AR5) through well-managed pastures[1].

The great challenge for the expansion of LCA in Brazil is the integration of environmental criteria, technical assistance, and financial credit. In this sense, there are still many cultural, technical, and financial obstacles that discourage farmers, especially small farmers, from adopting these sustainable practices. The lack of access to technology, knowledge, and interest (risk aversion) in LCA practices, as well as difficulties accessing credit or loans, are a consequence of little or non-existing technical assistance to support farmers in adapting their production systems.

The current state of knowledge of CF under major agricultural systems in Brazil

Beef cattle production

The beef cattle production system is the most studied due to the constant pressure to reduce GHG emissions. Enteric fermentation in central-west and southern Brazil contributed more than 90% of the CF[18,28]. In contrast, the contributions from inputs, fossil fuels, and electricity contributed 1%-11%[18]. Additionally, the conversion of degraded pasture to a well-managed pasture and the introduction of crop-livestock-forest integration system (CLFIS) can reduce the CF of beef cattle by 5.9 kg CO_2eq per kg LW (live weight) in CLFIS and 9.1 kg CO_2eq per kg LW in the managed pasture, without taking into account the technical potential for C sequestration in the managed pasture (soil C) and CLFIS (soil C and *Eucalyptus* biomass C). Considering the potential for soil C sequestration in the managed pasture and CLFIS, the CF of beef cattle could be reduced to 7.6 and 28.1 kg CO_2eq per kg LW in managed pasture and CLFIS, respectively[29].

In turn, other studies have shown that some practices can be adopted to reduce the CF: (1) supplementation of the animal's diet with rations in the dry season, as this enables greater live weight gain during this phase; (2) reducing the slaughter weight, which subsequently reduces the animal's grazing time; (3) increasing the weaning rates; (4) pasture management with the introduction of legumes, which reduces the need for nitrogen fertilization, in addition to improving the nutritional quality of food; (5) introduction of high-yielding tropical forage species and intensively managed pastures; (6) introduction of winter and summer grasses; (7) improving the forage nutritive value; (8) replacing road transport units with more modern vehicles in the industrial phase; and (9) implementing an integrated crop-livestock system[28,30].

The confinement system in dairy cattle production in southern Brazil presented lower CF when compared to the semi-confinement and pasture-based system (CF per kg of milk with energy correction). The factor which most contributed to CF in the confinement and pasture system was enteric fermentation, while in semi-confinement, it was the type of cattle feed[31].

Common bean (Phaseolus vulgaris)

Regarding beans, the CF per kilogram of beans produced in an integrated production system was 7.4% lower than that in a conventional system due to the use of inoculants to replace synthetic nitrogen

fertilization[32]. This study concluded that this little difference in CF between systems indicates the need to seek improvements in agronomic practices of integrated systems aiming at better results.

Soybean

In the case of Brazilian soybean, the results presented by Escobar *et al.*[33] show great variability due to differences in land-use dynamics, growing conditions, and supply chain configurations up to the stage where soybean and its derivatives are delivered to importing countries. These authors and Persson *et al.*[34] highlighted that the loss of natural vegetation related to land-use change was the factor that contributed most to the increase in CF in soybeans. Additionally, Lathuillière *et al.*[35] pointed out that the decline in deforestation in the Mato Grosso region in the first decade of this century suggested a change in the soybean production system from an extensification system (agricultural expansion in natural ecosystems) to one based on intensification (increased productivity of the available land), which led to an increase in CF for this crop, even though there is no application of nitrogen fertilization due to the practice of inoculation with nitrogen-fixing bacteria and Brazilian soybeans are planted in a no-tillage system[24].

Vegetable crops

Pereira *et al.*[36] found interesting results in vegetable crops. The CF to produce 1 kg of vegetables in a consortium was approximately one-fifth that of monocultures, and sharing infrastructure (construction of greenhouses) and optimizing inputs in the consortium were the main GHG mitigators. They also stated that producing vegetables in a greenhouse, predominantly carried out in monoculture, significantly contributes to GHG emissions associated with agriculture in Brazil. The CF was also evaluated in yellow melon exporting farms (they account for about 99% of Brazilian exports), and the estimated value was 710 kg CO_2eq/t of exported melon. The authors suggested that this value could be reduced by 44% if melon production were located in pre-existing agricultural areas, as nitrogen fertilization would be reduced and no plastic trays would be used in melon production[37].

Coffee and Cocoa-cabruca AFS

In coffee monoculture, the CF represents 5% of emissions in the southeast region of Brazil related to agriculture, with the use of water for irrigation being the main factor that contributes to the increase in CF[38]. Martins *et al.*[38] suggested that carbon sequestration in coffee tree biomass should be considered to reduce the CF. Schroth *et al.*[39] found that agricultural intensification in cocoa-cabruca AFSs (cocoa plantations implanted under natural forest) in southern Bahia reached twice the regional average yield mainly through mineral fertilization, which was compatible with maintaining a low CF related to inputs, close to 0.25 kg CO_2eq kg^{-1} of cocoa seeds. They also demonstrated that shade tree management (a shade level of up to 55%) could increase C stocks in plant biomass, thus constituting another positive contribution to climate change mitigation, which could add conservation value to cabruca systems in Bahia.

All of these case studies indicated the main sources of greenhouse gases in some products of Brazilian agriculture at the farm scale. However, we need to develop research lines for an integrated assessment of the different land use systems at a landscape scale in the different biomes for a better understanding of agricultural production in the context of the environmental impacts and sustainability of the production chain. Thus, we can enter the low-carbon agriculture route, aiming to protect the environment for future generations while meeting urgent needs for food.

Compensation for GHG emissions

Compensation of GHG emissions can also be achieved by carbon sequestration (C); in particular, soil C stock, as a process of converting atmospheric CO_2 into stable soil organic C through forming organomineral

complexes, can compensate for GHG emissions, mainly because soil stores 2-3 times more C than the atmosphere. Studies on soil C stock as a measure to offset GHG emissions have grown in Brazil, with a wide range of 20-460 Mg C ha^{-1} [Table 3]. This wide variation in C stocks is due to the adopted management systems, the soil texture, relief, sampling depth, age of land-use systems, climate conditions, land-use history, and chemical composition of plant residues.

Agricultural land under no-tillage, mainly in crop rotation or intercropping systems, plays an important role in promoting soil erosion control and reducing soil organic C losses, favoring aggregation and, therefore, soil C stabilization through greater physical protection against the action of microorganisms[24,40]. Besides, the adoption of no-till and no burning of crop residues can help to restore soil carbon, particularly during the summer season and when farmers leave large amounts of crop residues on the soil surface.

Land-use systems based on trees and pastures (well managed and/or under grazing) showed a higher soil C stock due to the continuous addition of residues (above- and below-ground), and also because most of them have not suffered from soil disturbance for over 20 years. It is worth mentioning that pasture management (by reducing stocking rate and/or using a mixture of pastures) promoted an increase of close to 40% in the C stock up to 1 m depth [Table 3]. Salgado *et al.*[41] reported that the C stock at 1 m depth in the soil under rubber plantation was 51 and 89 Mg ha^{-1} higher than the stocks of rubber tree + açaí and rubber tree + cacao agroforestry systems (AFSs), respectively, in southern Bahia, Brazil. However, the AFSs showed a higher amount of stable C (in the range of 41%-54% of C occluded in macro- and micro-aggregates) than the rubber tree plantation (32%). These results emphasize aggregates as a C storage compartment in the soil, and therefore the relevance of evaluating the extent of C storage in different fractions of soil aggregates up to 1 m depth. Thus, to increase the C reservoir in the soil, it is necessary to adopt management practices that favor a positive C balance and its persistence in the soil. In this sense, conservationist production systems must be adopted on a large scale in order to mitigate GHG emissions in the Brazilian agricultural and forestry sector.

Brazil is one of the few countries in the world that integrates in the same area different production systems (grain, fiber, bioenergy, livestock, and forest production) in a consortium, rotation, or succession, with mutual benefits for all activities. This technology optimizes land use, increases productivity, provides market product diversification, plays an important role in food security and the efficient use of natural resources, and is a viable strategy to improve farm income. Thus, these integrated systems constitute a landscape mosaic with enormous potential for reducing CF.

In this context, we highlight the multistrata agroforestry systems that present a forest-like structure with a highly diversified landscape that could be interconnected by forest remnants. They are a potential supplier of fruits, firewood, wood, latex, fodder, and ecosystem services for increasing biodiversity and promoting soil health, and improving water quality, in addition to the benefits mentioned above[4]. These systems would be an appropriate technology for improving the living standard of household in an agricultural region that would be based on the natural resources conservation and, therefore, promising for the consolidation of climate-friendly agriculture [Figure 2].

CONCLUSIONS AND PERSPECTIVES

Sustainable rural development programs and activities are increasing in Brazil with the improved adoption of the LCA Plan technologies, resulting in a 154% expansion in area and a 113% increase in CO_2 mitigation in the atmosphere. These activities are currently confined to some regional segments and a small number of farmers, but they should be disseminated for wider adoption on a national scale. To achieve this, it is

Table 3. Soil C stock (Mg ha^{-1}) under different land-use systems

Land use systems	Bioma	Depht (cm)	C stock	Ref.
CT - sugarcane	Cerrado; Atlantic Forest	100	77-168	Oliveira *et al.*[42]
CT - soybean	Cerrado	30	~50	Siqueira-Neto *et al.*[43]
CT - crop rotation	Cerrado	30	50-60	Carvalho *et al.*[44]
CT - maize	Cerrado	100	~78	Santos *et al.*[45]
NT - crop rotation	Cerrado	30	60-65	Siqueira-Neto *et al.*[43]
NT - intercrop	Cerrado	40	45-60	Gmach *et al.*[46]
NT - maize	Cerrado	100	~79	Santos *et al.*[45]
Pasture	Amazon Cerrado	30	55-75	Siqueira-Neto *et al.*[43] Carvalho *et al.*[44] Rittl *et al.*[47]
Pasture	Cerrado	40	70-75	Gmach *et al.*[46]
Pasture	Cerradão	100	100-460	Oliveira *et al.*[42] Pinheiro *et al.*[48] Tonucci *et al.*[49]
Pasture	Atlantic rainforest	100	150-220	Salgado *et al.*[41] Oliveira *et al.*[50] Monroe *et al.*[51] Vicente *et al.*[52]
Integrated crop-livestock system	Cerrado	30	60-73	Carvalho *et al.*[44]
Silvopasture	Cerrado	100	19-420	Pinheiro *et al.*[48] Tonucci *et al.*[49]
Cacao cabruca AFS	Atlantic rainforest	100	180-330	Monroe *et al.*[51] Gama-Rodrigues *et al.*[53]
Cacao + erithrina[1] AFS	Atlantic rainforest	100	174-310	Oliveira *et al.*[50] Monroe *et al.*[51] Gama-Rodrigues *et al.*[53]
Cacao + rubber tree AFS	Atlantic rainforest	100	92-206	Salgado *et al.*[41] Oliveira *et al.*[50] Monroe *et al.*[51]
Rubber tree + Açaí[2] AFS	Atlantic rainforest	100	~130	Salgado *et al.*[41]
Rubber tree plantation	Atlantic rainforest	100	180-220	Salgado *et al.*[41] Oliveira *et al.*[50] Vicente *et al.*[52]
Eucalyptus	Cerrado	40	~50	Gmach *et al.*[46]
Eucalyptus	Cerradão	100	180-404	Pinheiro *et al.*[48] Tonucci *et al.*[49]
Eucalyptus	Atlantic rainforest	100	145-160	Vicente *et al.*[52]
Native vegetation	Cerrado	30	63-75	Siqueira-Neto *et al.*[43] Carvalho *et al.*[44]
Native vegetation	Cerrado	40	~75	Gmach *et al.*[46]
Native vegetation	Cerrado	100	75-94	Santos *et al.*[45]
Native vegetation - an intermediate Cerrado with trees	Cerradão	100	94-414	Oliveira *et al.*[42] Pinheiro *et al.*[48] Tonucci *et al.*[49]
Natural forest	Amazon	30	56-70	Carvalho *et al.*[44] Rittl *et al.*[47]
Natural forest	Atlantic rainforest	100	83-260	Salgado *et al.*[41] Oliveira *et al.*[50] Monroe *et al.*[51] Vicente *et al.*[52] Gama-Rodrigues *et al.*[53]

[1]*Erythrina* sp.; [2]*Euterpe oleracea*. CT: Conventional tillage; NT: no tillage.

necessary to involve the local community, local and national NGOs, the private sector, and federal and municipal agencies and intensify public policies for access to rural credits and innovations in diffusing

Figure 2. Multistrata agroforestry systems as a model of low-carbon agriculture in Brazil: (A) cacao + rubber tree with food crops in the initial phase; (B) cacao + rubber tree in the mature phase; and (C) cacao + coffee + peach palm.

technologies. Large-scale adoption of conservationist agriculture practices by the farming community will generate economic opportunities leading to financial gains from the commercialization of carbon credits and payment for environmental services.

On the other hand, the challenge of low-carbon agriculture in Brazil is to expand the production of food, bioenergy, and other products to meet future demands with less dependence on the use of inputs while also saving land and protecting natural ecosystems. To do so, future research actions to reduce carbon footprints should prioritize sustainable intensification through a combination of agricultural intensification (production value) with ecological intensification (conservation value) at the landscape scale. High emphasis should be placed on the role of biological processes in controlling pests and diseases and on nutrient cycling for maximizing the input-use efficiency, thereby allowing a sharp reduction in production costs. In turn, this can increase the economic and ecological resilience of agricultural regions in Brazil. In this context, low-carbon agriculture can be considered an environmentally friendly and climate-smart technique.

DECLARATIONS

Authors' contributions

Conceived and wrote the manuscript: Gama-Rodrigues EF, Gama-Rodrigues AC
Responsible for the figures and graphical abstract: Alvarenga LCBR
Responsible for data collection: Gama-Rodrigues EF, Gama-Rodrigues AC, Vicente LC, Müller MW, Partelli FL, Gonçalves JLM, Freitas LS, Alvaristo DM, Cruz IB, Souza ING, Faitanin MA

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Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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