Food and Agriculture Emissions

Problems and opportunities in agriculture

Assignments

Brightspace discussion question:

“Would you consider making changes to your diet based on its impact on climate? Why or why not?”

Due this Friday by 5pm.

Second programming assignment on predicting building energy use

Due Friday the 17th by midnight.

Climate change in the news

Climate change in the news

Chick-fil-A tests its first plant-based sandwich

By DEE-ANN DURBIN February 9, 2023

Chick-fil-A is jumping on the plant-based bandwagon.

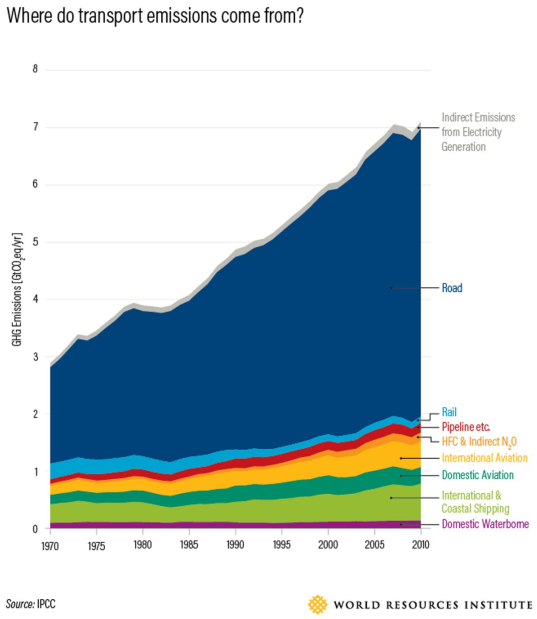
The Atlanta chain said Thursday that it's testing its first plant-based entrée — a breaded cauliflower sandwich — at restaurants in Denver; Charleston, South Carolina; and the Greensboro, North Carolina, area. The test begins Feb. 13.

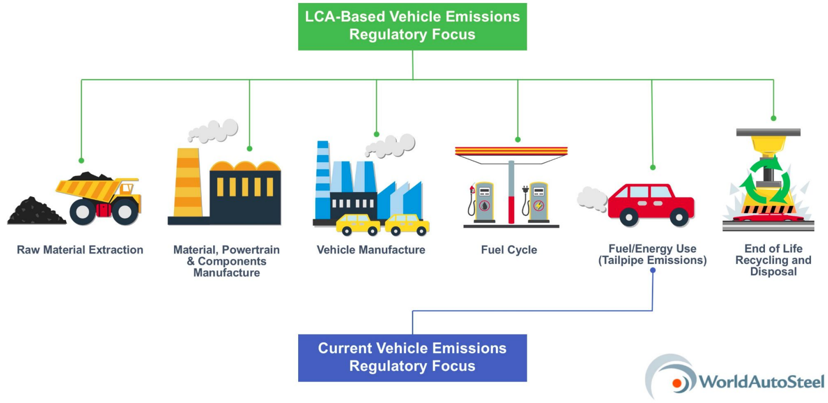
Chick-fil-A said its culinary team spent four years developing the sandwich after guests told the chain they wanted to add more vegetables to their diets. Chick-fil-A tested mushrooms, chickpeas and chopped vegetables formed into patties but kept returning to cauliflower for its mild flavor.

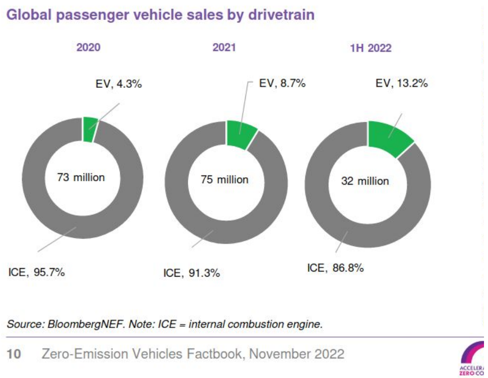
Like Chick-fil-A's signature chicken sandwich, the cauliflower steak is marinated, breaded, pressure-cooked and then served on a bun with two pickle slices.

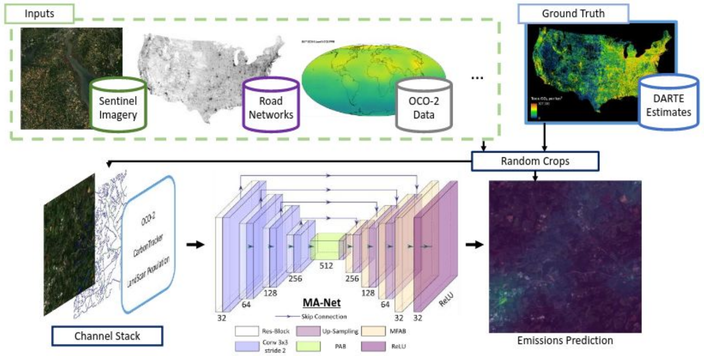
Chick-fil-A is a relative latecomer to the plant-based fast food scene. Burger King started selling its Impossible Whopper — featuring a plant-based burger made by Impossible Foods — in 2019. Starbucks launched an Impossible sausage sandwich in 2020. McDonald's debuted its McPlant burger — developed with Beyond Meat — in the United Kingdom in 2021. And KFC began selling Beyond Meat nuggets last year.

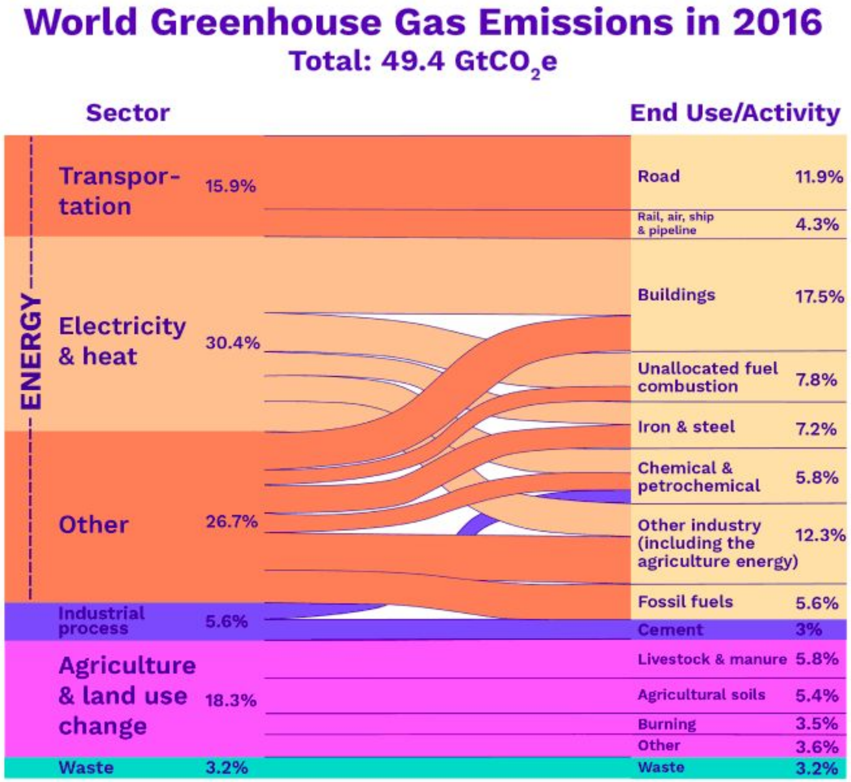
Recap


Where do transport emissions come from?
8
7
6
5
4
3
2
1
0
GHG Emissions [GtCO2eq/yr]
1970
1975
1980
1985
1990
1995
2000
2005
2010
Indirect Emissions from Electricity Generation
Road
Rail
Pipeline etc.
HFC & Indirect N2O
International Aviation
Domestic Aviation
International & Coastal Shipping
Domestic Waterborne
Source: IPCC
WORLD RESOURCES INSTITUTE


LCA-Based Vehicle Emissions Regulatory Focus
Raw Material Extraction
Material, Powertrain & Components Manufacture
Vehicle Manufacture
Fuel Cycle
Fuel/Energy Use (Tailpipe Emissions)
End of Life Recycling and Disposal
Current Vehicle Emissions Regulatory Focus
WorldAutoSteel


Global passenger vehicle sales by drivetrain
2020
2021
1H 2022
EV, 4.3%
EV, 8.7%
EV, 13.2%
73 million
75 million
32 million
ICE, 95.7%
ICE, 91.3%
ICE, 86.8%
Source: BloombergNEF. Note: ICE = internal combustion engine.
10 Zero-Emission Vehicles Factbook, November 2022

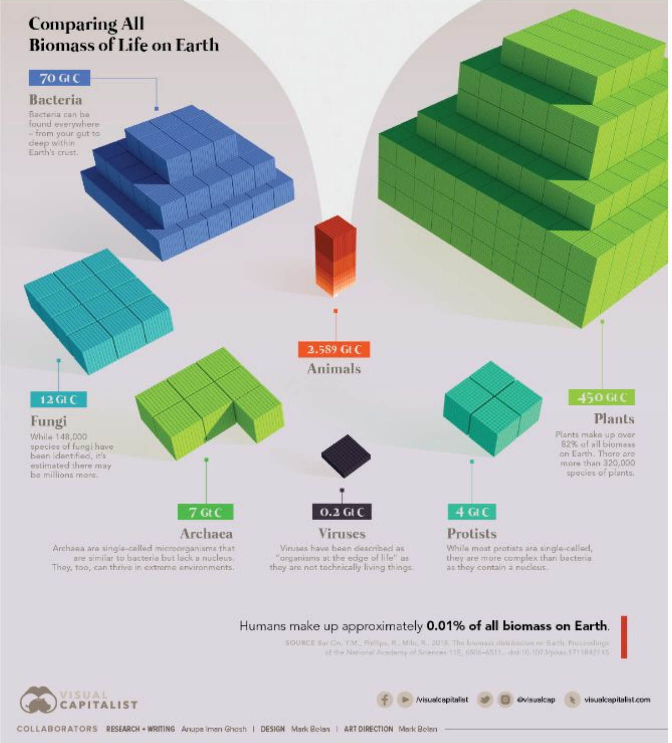

Inputs
Sentinel Imagery
Road Networks
OCO-2 Data
...
Ground Truth
DARTE Estimates
Random Crops
Channel Stack
MA-Net
Emissions Prediction

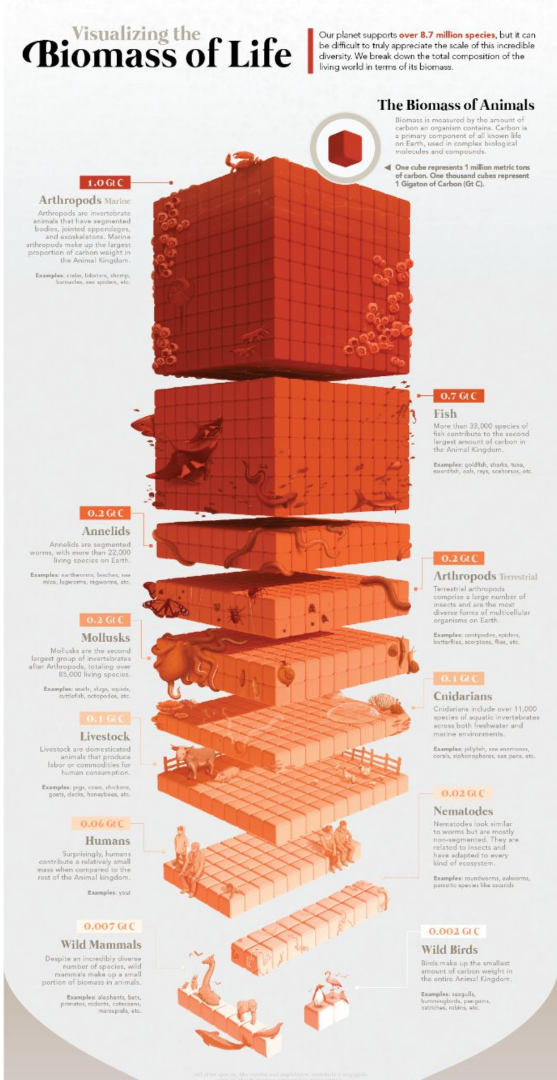


Source: Greenhouse gas emissions on Climate Watch. Available at: https://www.climatewatchdata.org

Understanding planet biomass

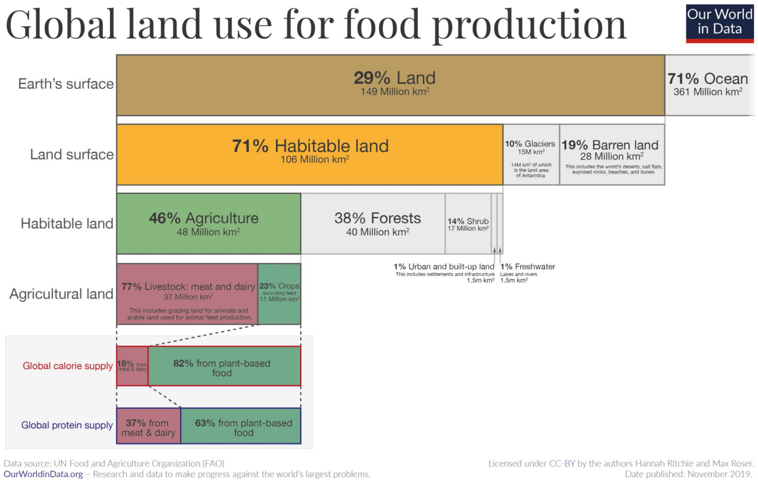
Biomass is measured in terms of the amount of carbon in a group of living things.

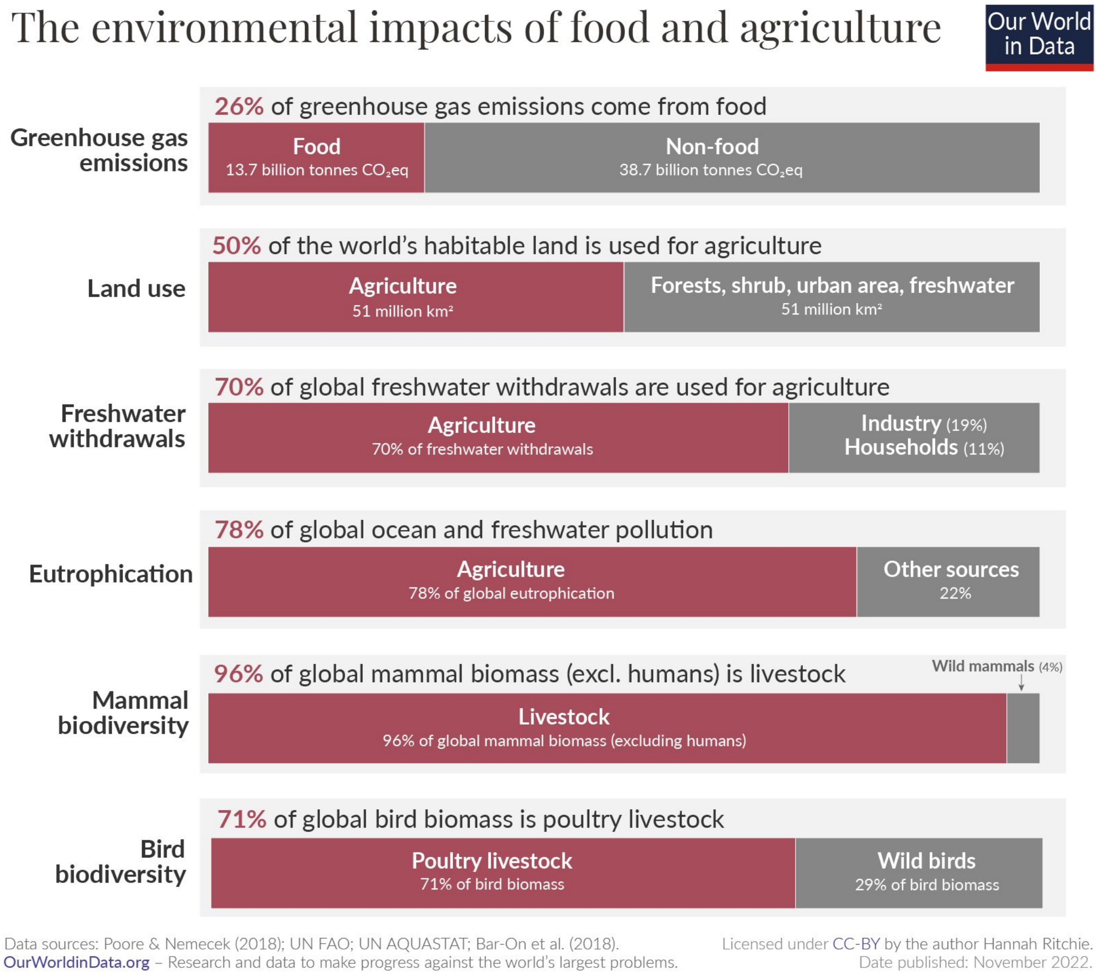




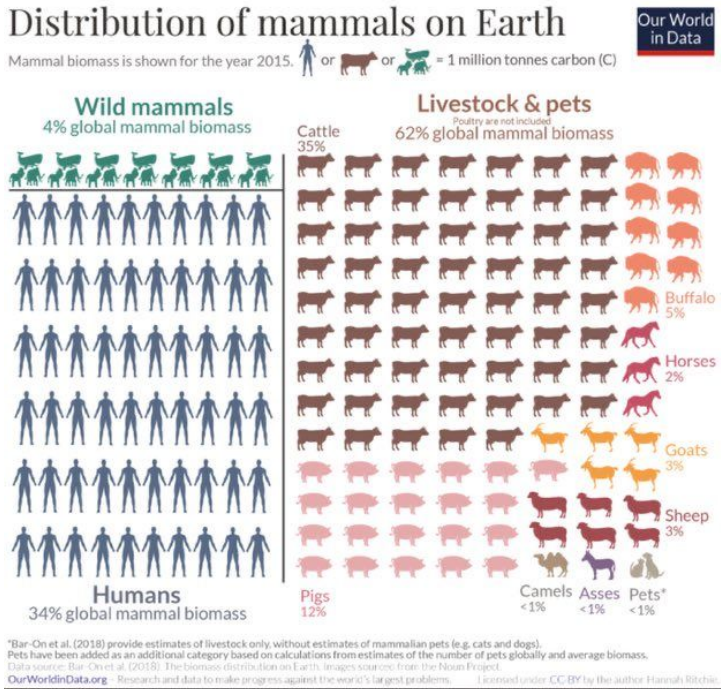
https://www.visualcapitalist.com/all-the-biomass-of-earth-in-one-graphic/

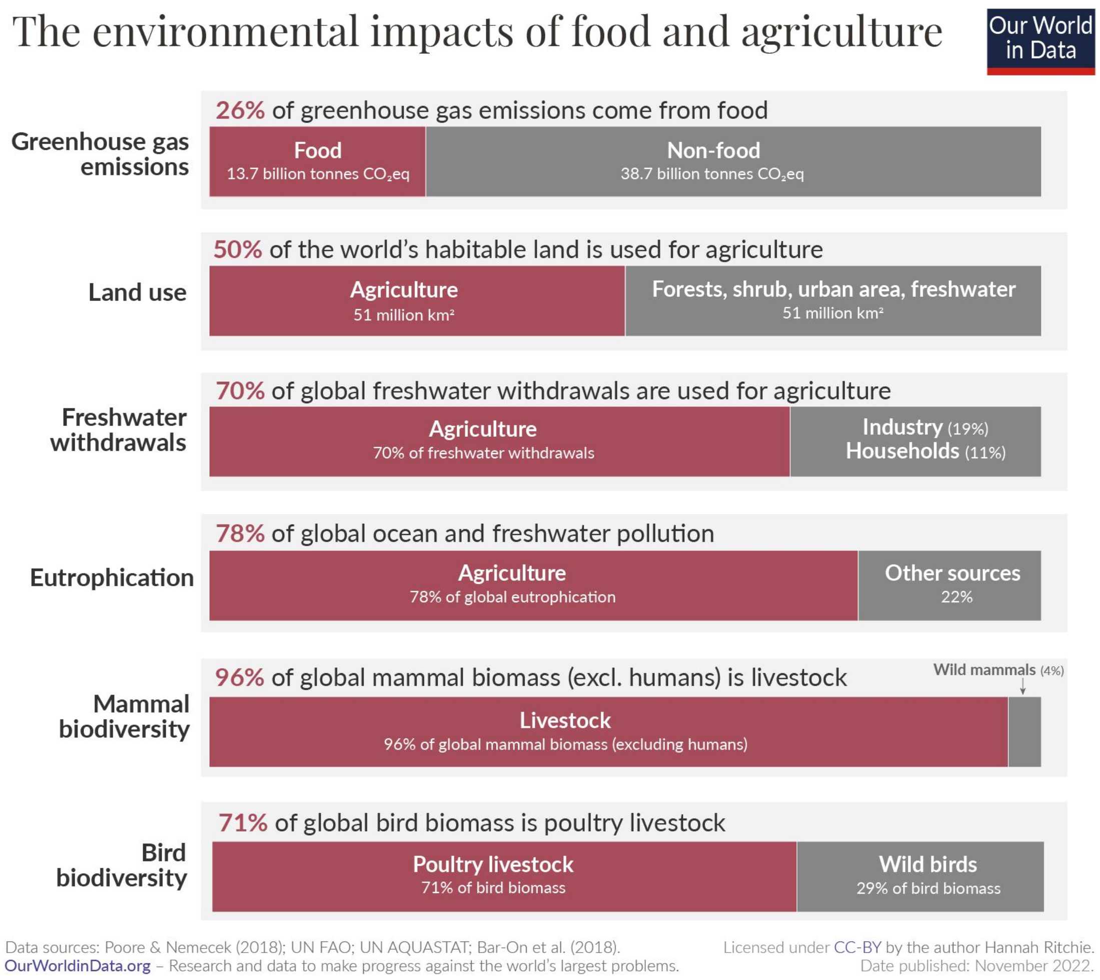
Agriculture has a large impact on the planet





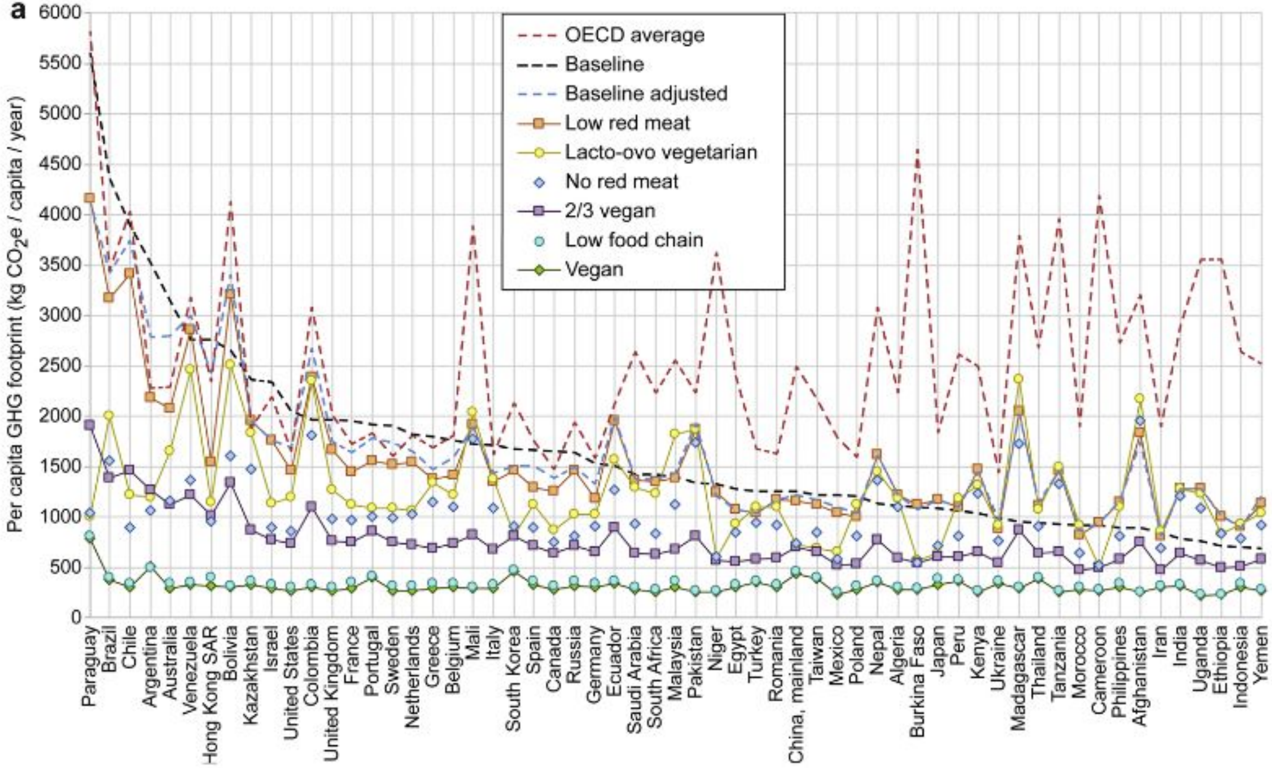
Agriculture has a large impact on the planet





Per capita emissions per country

Food emissions don’t exactly follow the normal trend of wealthier nation = higher emissions

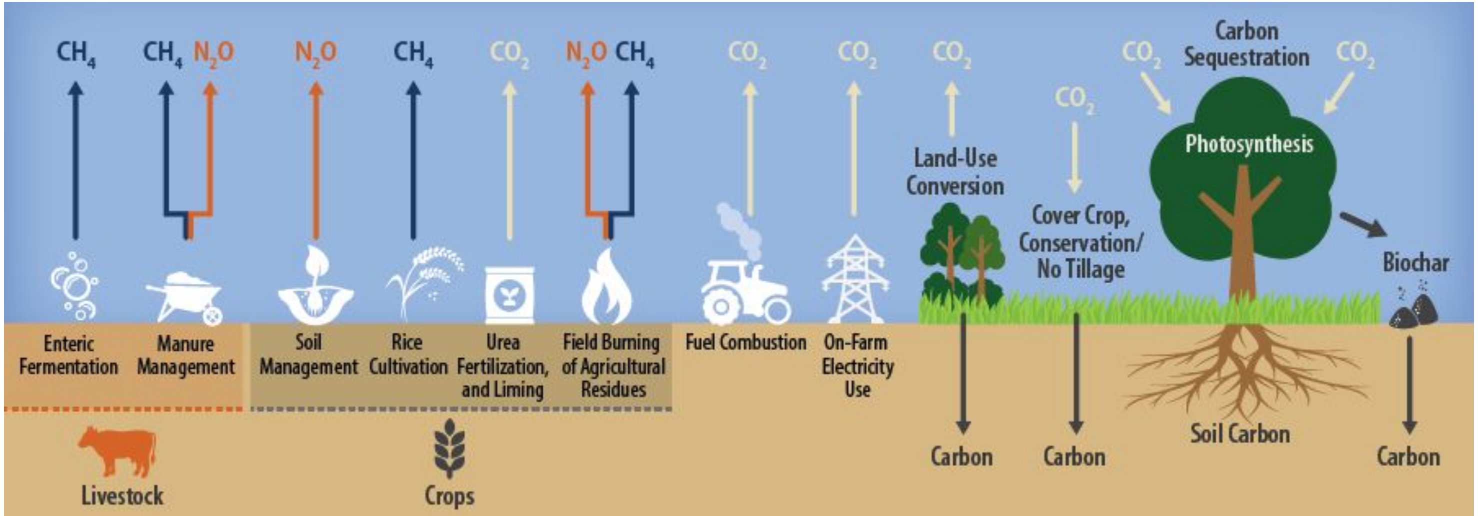


Agriculture accounted for 10% of the EU’s total greenhouse-gas emissions in 2012. A significant decline in livestock numbers, more efficient application of fertilisers, and better manure management reduced the EU’s emissions from agriculture by 24% between 1990 and 2012.

However, agriculture in the rest of the world is moving in the opposite direction. Between 2001 and 2011, global emissions from crop and livestock production grew by 14%. The increase occurred mainly in developing countries, due to a rise in total agricultural output. This was driven by increased global food demand and changes in food-consumption patterns due to rising incomes in some developing countries. Emissions from enteric fermentation increased 11% in this period and accounted for 39% of the sector's total greenhouse-gas outputs in 2011.

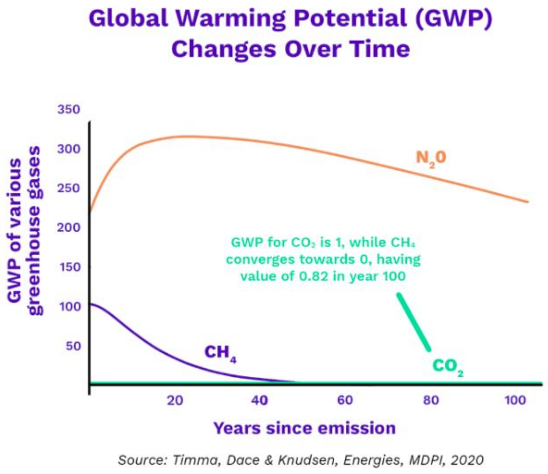
Agriculture: sources and sinks

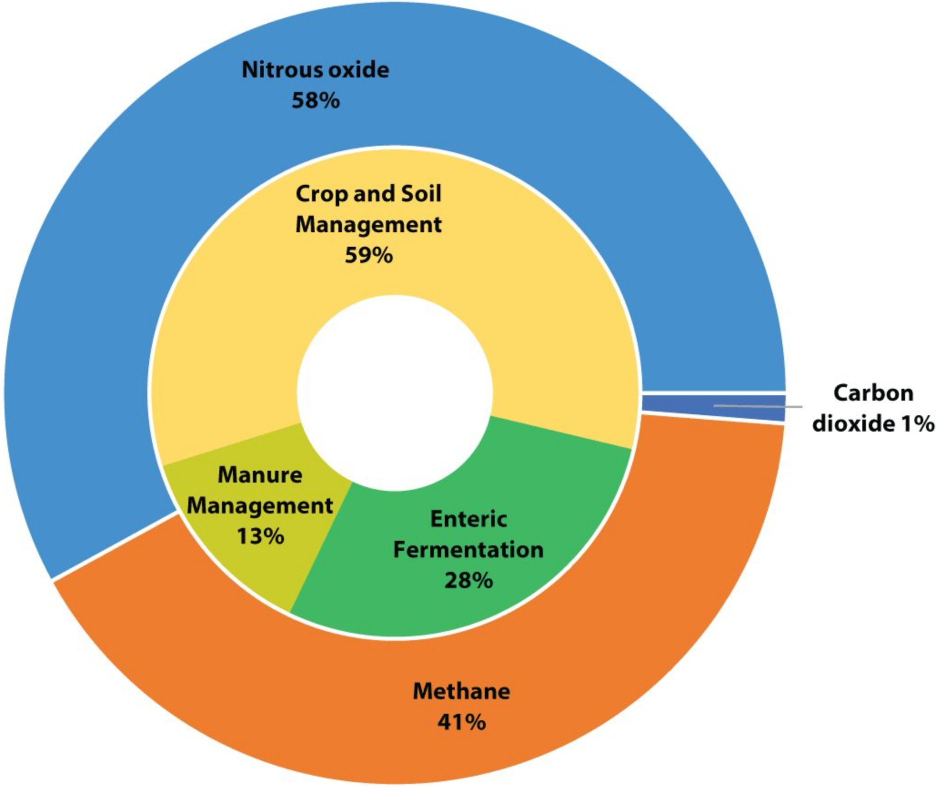
- Farming of plants and animals can capture as well as release CO2.
- Farming requires land that may have been used for other purposes
- Modern farming practices lead to far more emissions than reductions in GHGs



Emissions (direct) from agriculture

Carbon dioxide makes up only a small fraction of emissions from the agriculture industry.

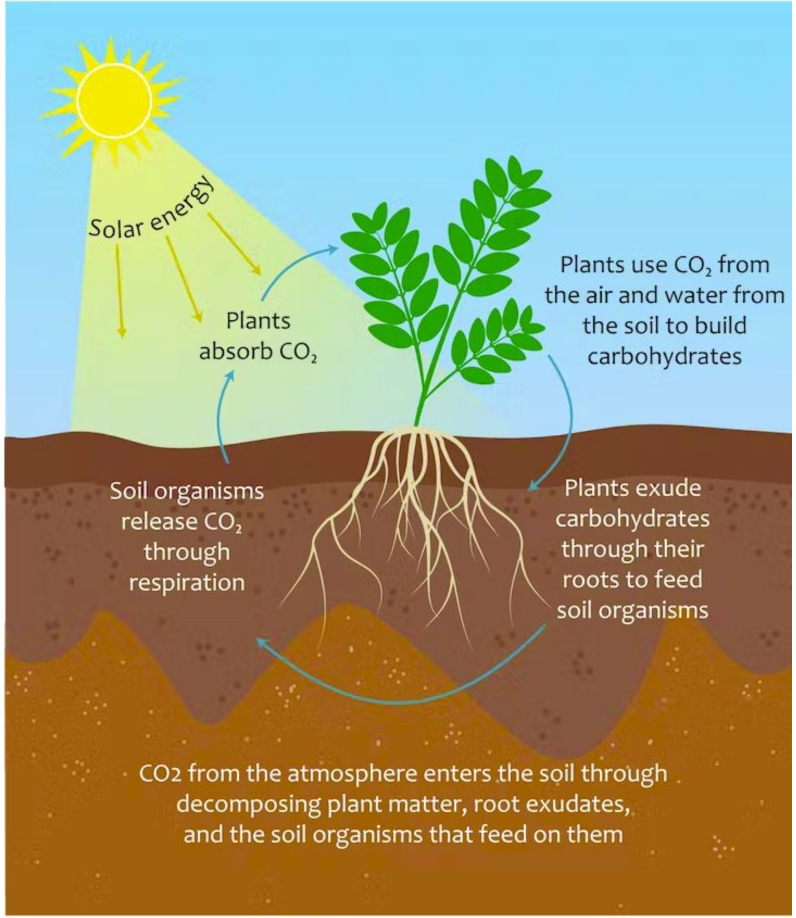




https://extension.missouri.edu/publications/g310

Crop and Soil Management

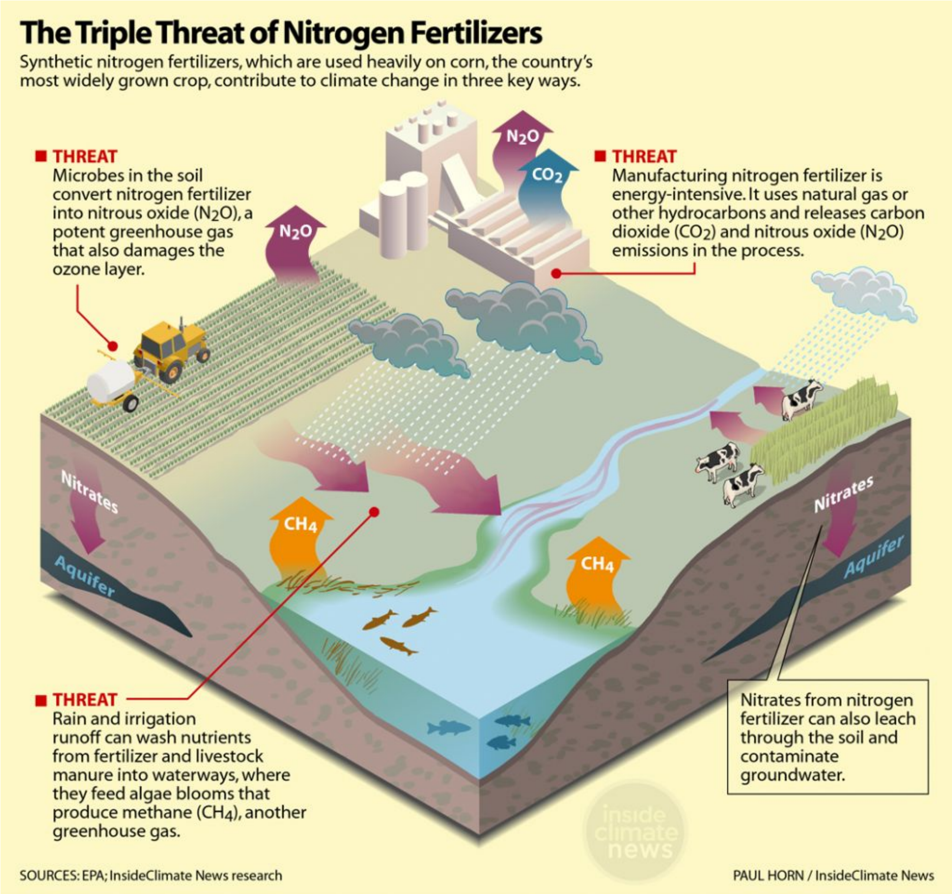
Soils store and release carbon through interaction with plants, animals, and microbes



How carbon cycles into and out of soil. Jocelyn Lavallee, CC BY-ND

Crop and Soil Management

Modern fertilizer production and use causes a variety of emissions, as well as other environmental problems.



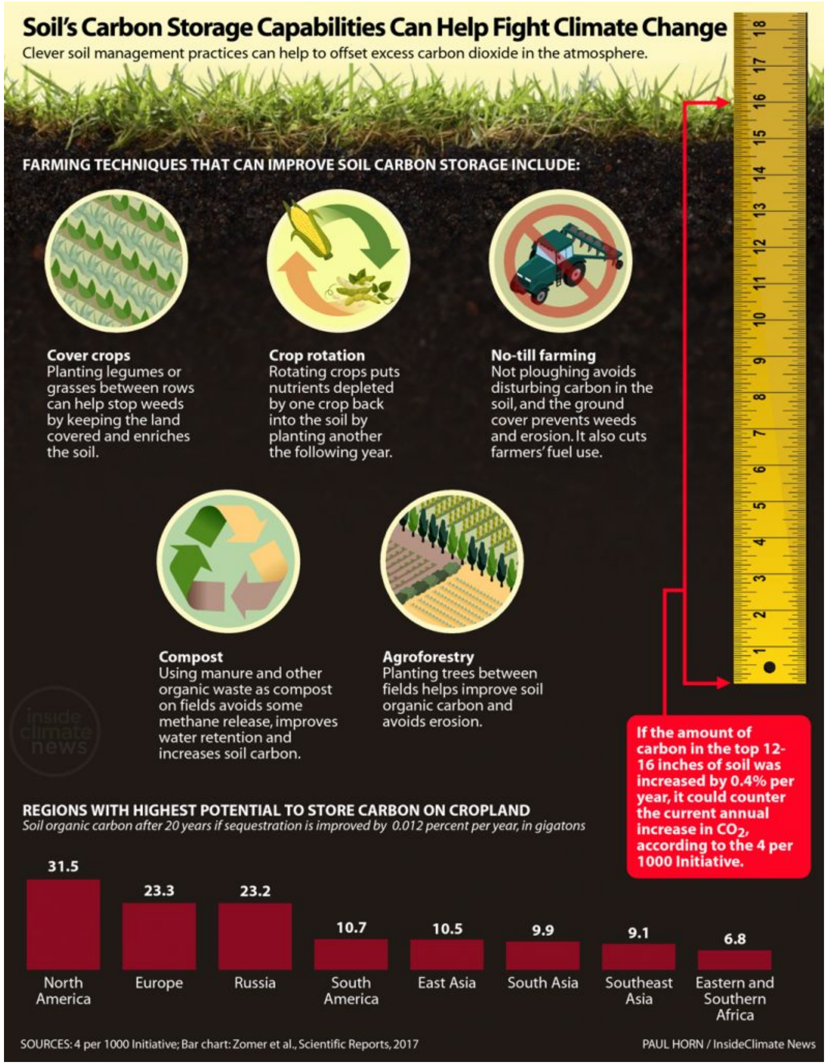
https://insideclimatenews.org/news/24102018/infographic-farm-soil-carbon-cycle-climate-change-solution-agriculture/

Crop and Soil Management

Better agricultural practices (sometimes called regenerative farming) can help soil sequester more carbon.

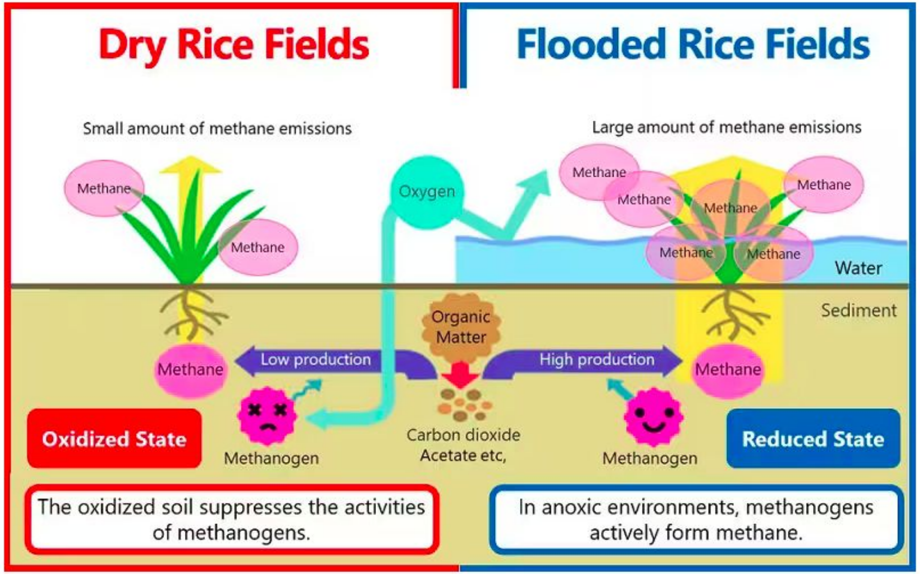
Because of the large amount of land dedicated to farming, small changes can have big impacts.

https://insideclimatenews.org/news/24102018/infographic-farm-soil-carbon-cycle-climate-change-solution-agriculture/



Crop and Soil Management

Rice paddies and their flooding is responsible for 10% of global methane release.

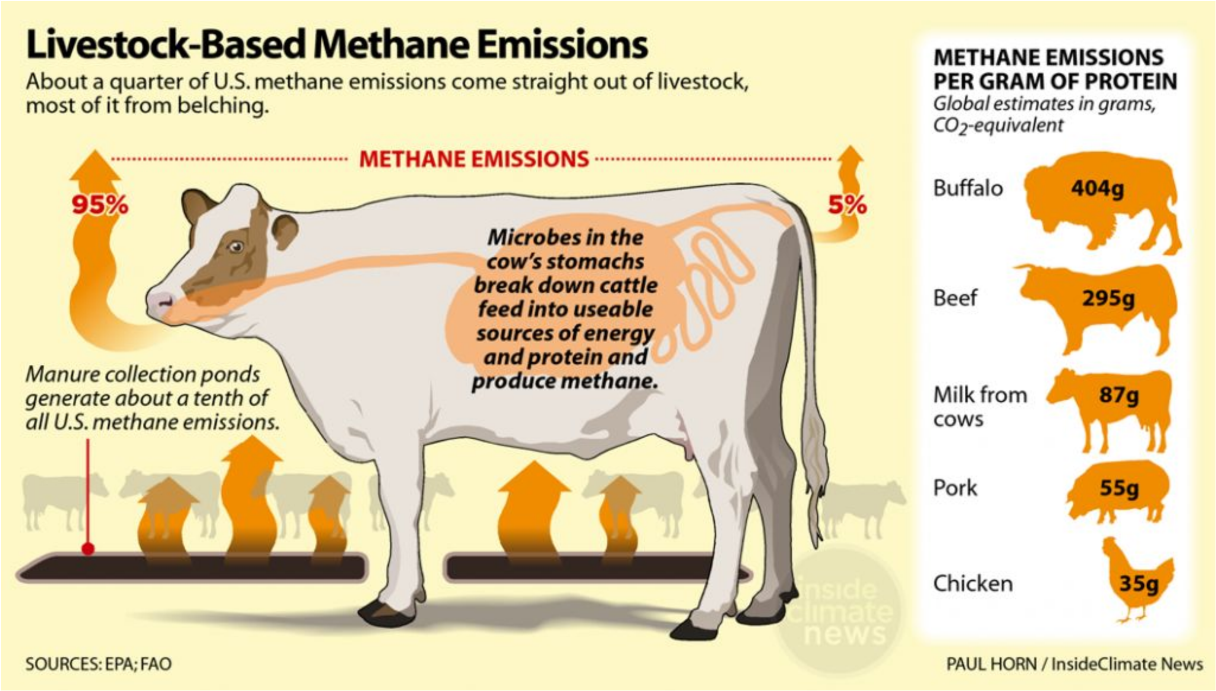


Mechanism of greenhouse gas emissions from agriculture (Source: NARO)

https://insideclimatenews.org/news/24102018/infographic-farm-soil-carbon-cycle-climate-change-solution-agriculture/

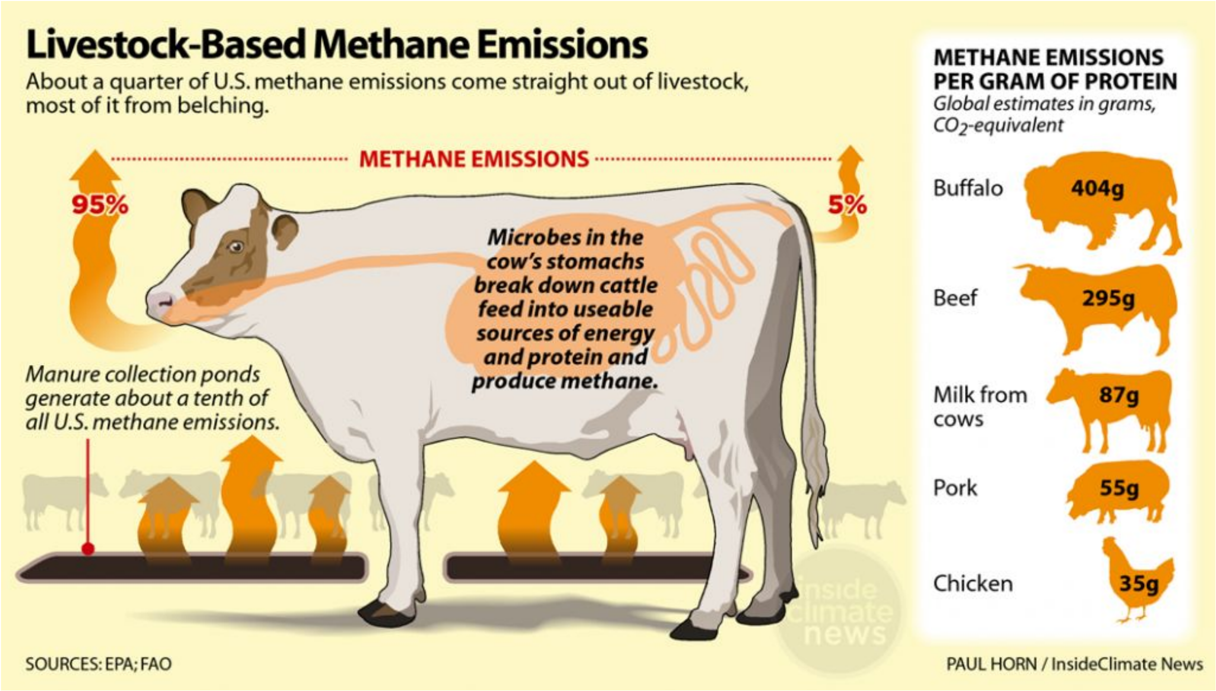
Enteric Fermentation and Manure

Digestive processes in ruminant animals such as cattle, sheep, goats, and buffalo, cause methane release.



Enteric Fermentation and Manure

Manure from large numbers of animals stored in piles creates anaerobic conditions and the release of methane and nitrous oxide.

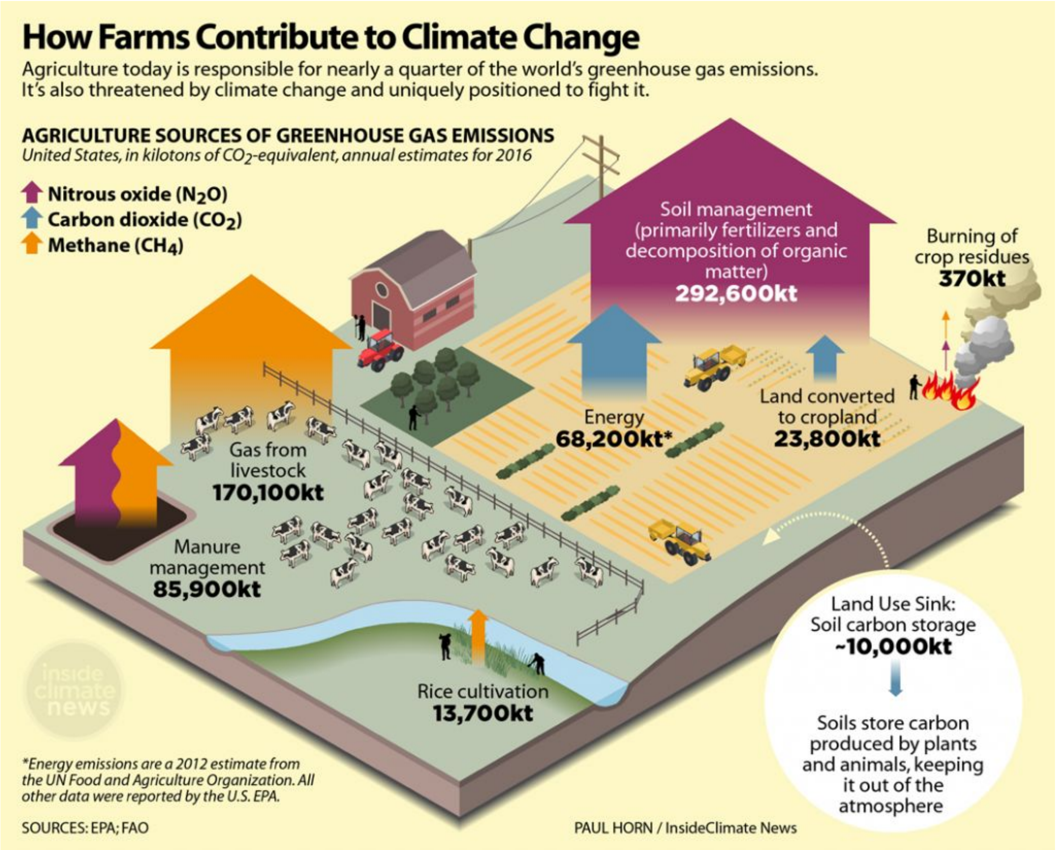


Indirect emissions from agriculture

Electricity

Burning of biomass

Land use changes



Indirect emissions from agriculture

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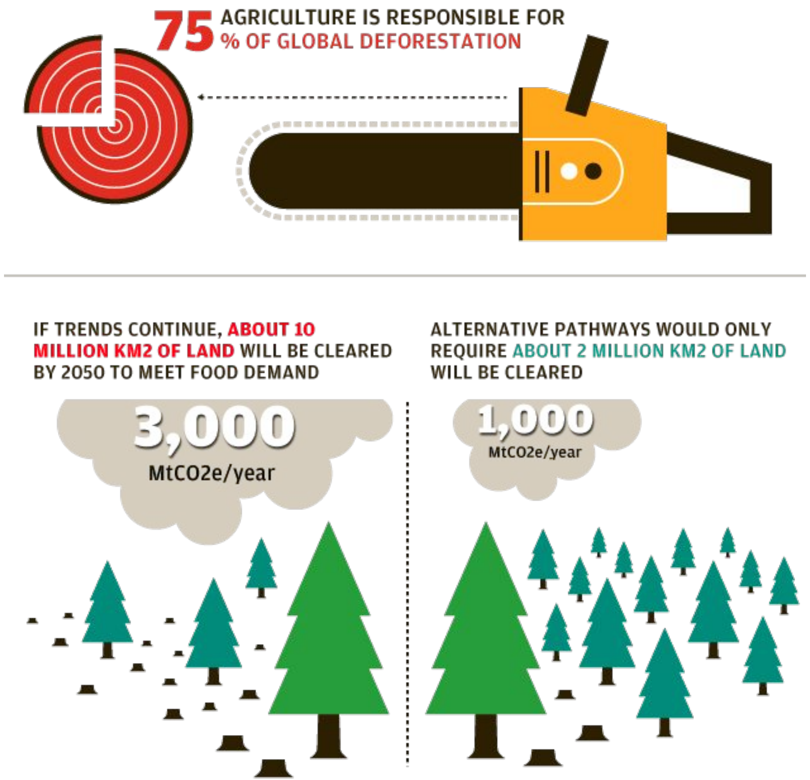
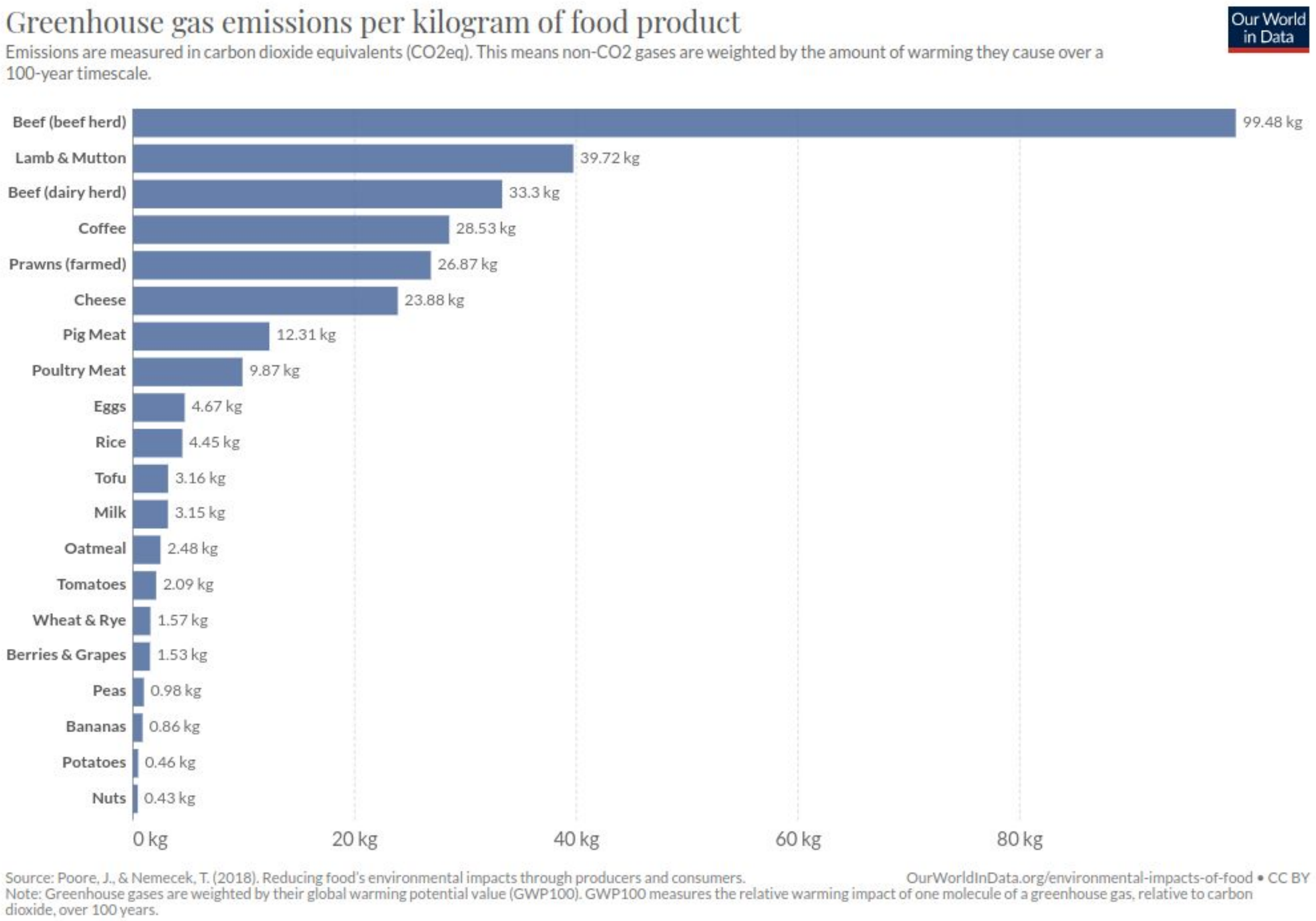


downtoearth.org

Emissions from specific foods



Emissions per 100g of protein

Emissions estimates have wide variability due to different farming practices.

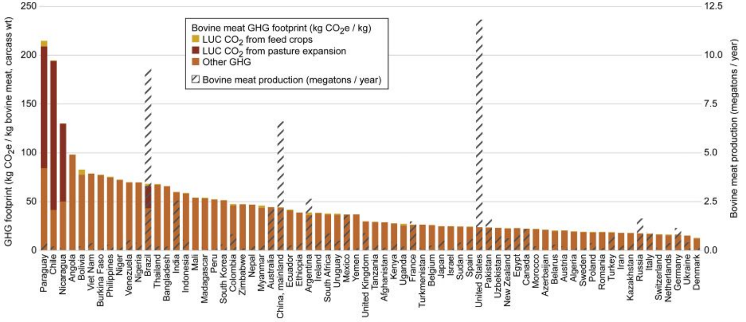
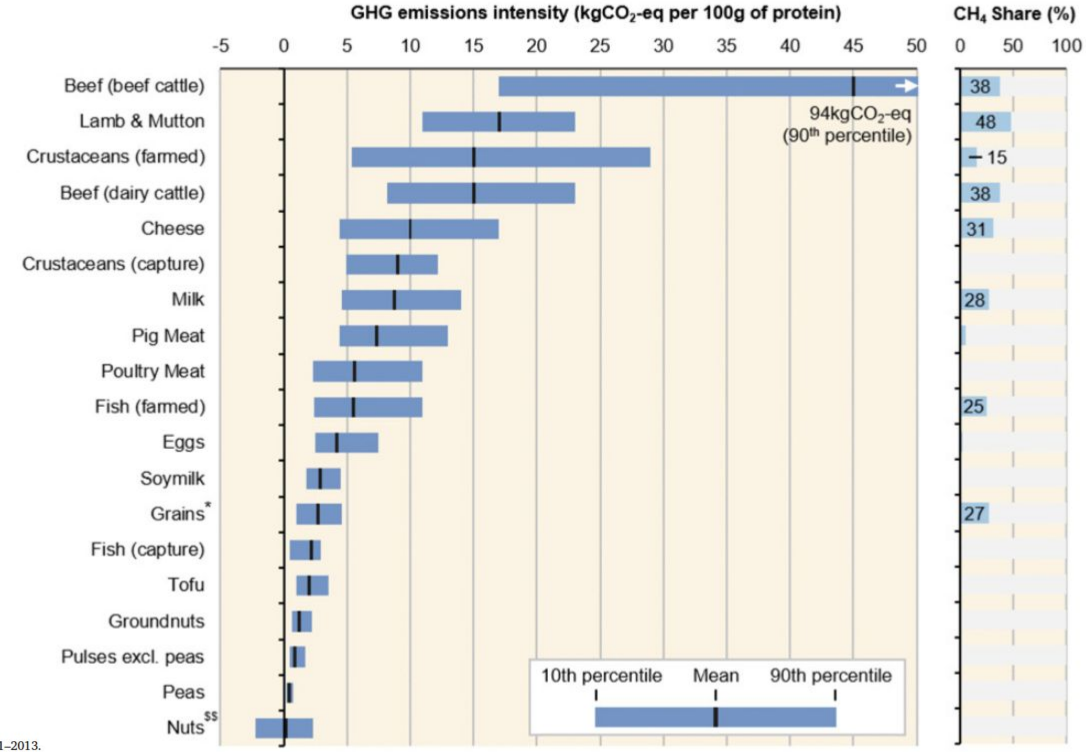
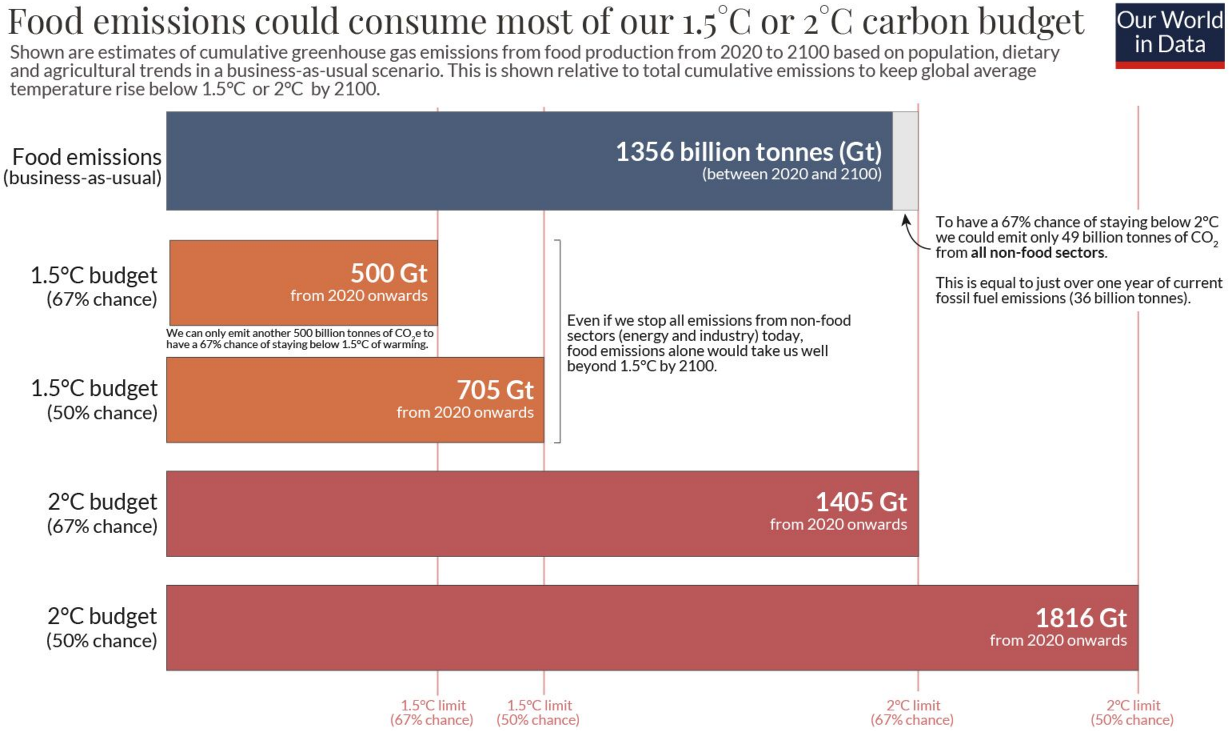


Fig. 3. Per-kilogram GHG footprints of bovine meat, by producing country, shown for countries that produced over 100 000 metric tons in 2011–2013.



Significant changes to agriculture are necessary to avoid unsustainable warming



Note: This is measured in global warming potential (GWP*) CO_2 warming-equivalents (CO_2-we).
Source: Michael Clark et al. (2020). Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets. *Science*.
OurWorldinData.org – Research and data to make progress against the world's largest problems.

What needs to be done, according to the IPCC

A change in diets (and culture)

Shifting consumption towards plant-based diets has “high mitigation potential”, says the report. There is *robust evidence* that “diets high in plant protein and low in meat and dairy” make for lower GHG emissions.

IPCC estimates with *high confidence* that shifts to sustainable healthy diets have a “technical potential” to reduce emissions by 3.6GtCO2e, with a range of 0.5 to 8GtCO2e.

Key enablers for these shifts could include creating “novel narratives” in the media and entertainment industry to “help to break away from the established values, discourses and the status quo”. These might portray plant-based diets as healthy and natural, for example.

The IPCC report explores other measures that could be used to influence choices in the food sector, including taxes or carbon pricing on food, both of which it says would be “regressive”, meaning they disproportionately burden poorer members of society. Instead, it points to options including marketing regulations, procurement policies, dietary guidelines, labelling and “nudges”.

https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-on-how-to-tackle-climate-change/

What needs to be done, according to the IPCC

New technologies

Beyond dietary changes, the report says there is *limited evidence* – but *high agreement* – that a suite of “emerging technologies” could bring “substantial reduction in direct GHG emissions from food production”. These include plant-based alternatives to animal products, cultured meat, and “controlled environment agriculture”, which it describes as ”hydroponic or aquaponic cultivation systems that do not require soil”.

These technologies typically have lower water, land and nutrient footprints, but as some of them are energy-intensive, they need to have access to low-carbon energy.

https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-on-how-to-tackle-climate-change/

What needs to be done, according to the IPCC

Focus on highest emitters globally

Global food supply chains have a strong influence on per-capita food consumption emissions, particularly for red meat and dairy, the report notes, such that the highest per-capita food-related emissions “do not correlate perfectly with the income status of countries”. In other words, even relatively poorer countries may have a high per-capita food footprint.

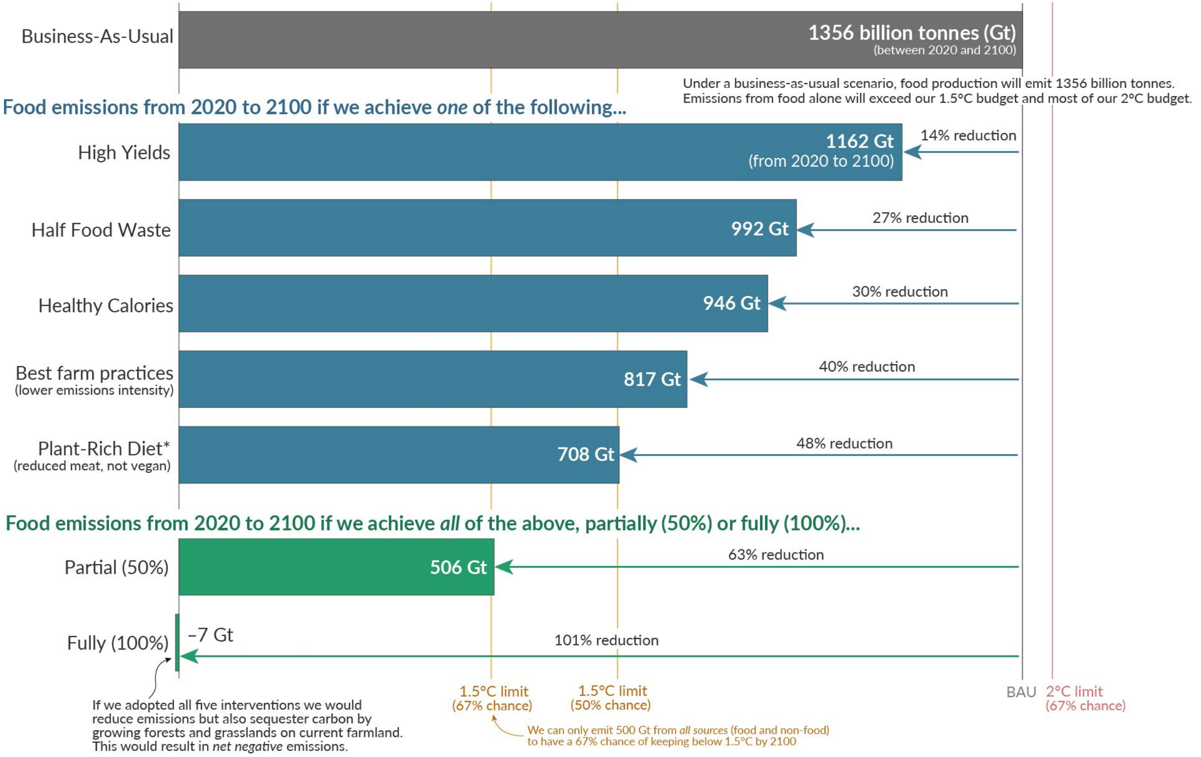
As a result, the report says “it is crucial to focus on high-emitting individuals and groups within countries, rather than only those who live in high-emitting countries, since the top 10% of emitters live on all continents and one third of them are from the developing world”.

https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-on-how-to-tackle-climate-change/

How can we reduce global greenhouse gas emissions from food?

Shown are estimates of cumulative greenhouse gas emissions from food production from 2020 to 2100 under a business-as-usual scenario, and five interventions to reduce emissions.
This is measured in global warming potential (GWP*) CO_2 warming-equivalents (CO_2-we).

Our World in Data



*Based on the EAT-Lancet Planetary Health diet which reduces but does not eliminate meat or dairy consumption.

Source: Michael Clark et al. (2020). Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets. *Science*.

OurWorldinData.org – Research and data to make progress against the world's largest problems.

Opportunities for ML in sustainable agriculture

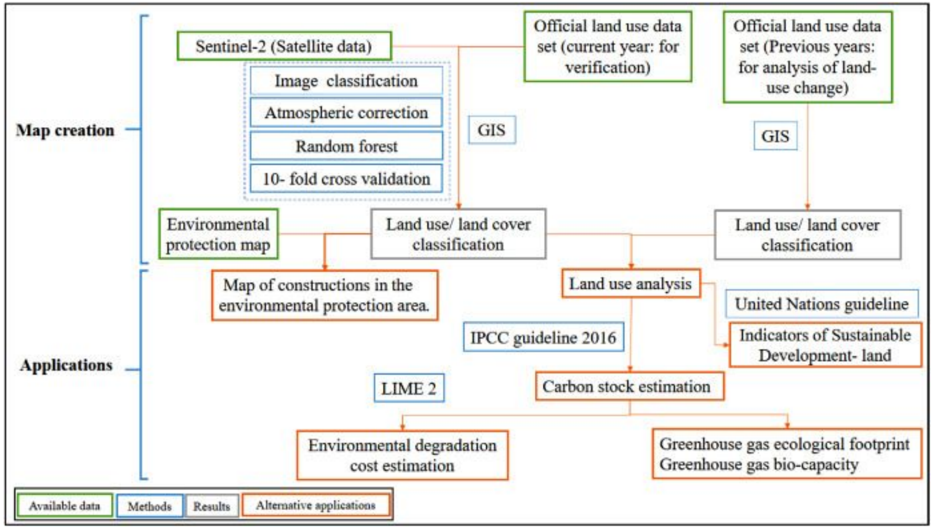
Opportunities for ML in sustainable agriculture

Monitoring land change to estimate emissions

Research article

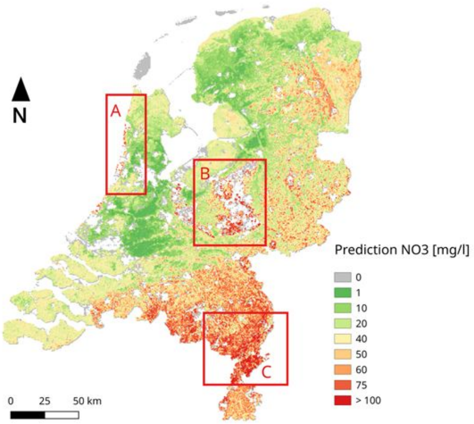
Integrating remote sensing and machine learning into environmental monitoring and assessment of land use change

Hong Anh Thi Nguyen [a b], Tip Sophea [c d e], Shabbir H. Gheewala [a b], Rawee Rattanakom [d], Thanita Areerob [d], Kritana Prueksakorn [c d f]



Opportunities for ML in sustainable agriculture

Tracking and predicting different types of emissions from soils



Zoom In Zoom Out Reset image size

Figure 7. Map of nitrate concentrations in the root zone leachate for the year 2017. Areas A, B, and C are areas with high predicted concentrations, marked for discussion.

PAPER • OPEN ACCESS

A machine learning based modelling framework to predict nitrate leaching from agricultural soils across the Netherlands

Job Spijker[1], Dico Fraters[1] and Astrid Vrijhoef[1]

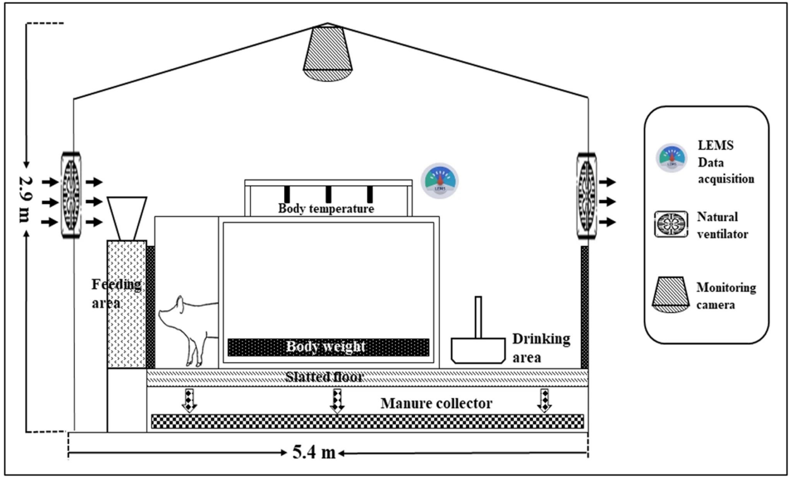
Published 14 April 2021 • © 2021 The Author(s). Published by IOP Publishing Ltd
Environmental Research Communications, Volume 3, Number 4
Focus on Reactive Nitrogen and the UN Sustainable Development Goals
Citation Job Spijker *et al* 2021 *Environ. Res. Commun.* **3** 045002
DOI 10.1088/2515-7620/abf15f

Conclusions

Using our RF predictive modeling framework, we created a map of nitrate concentrations leached from the root zone of agricultural soils across the Netherlands for the year 2017.With our model, we interpolate the nitrate concentrations measured at the farm level on a national scale. In our model, the most important variables for the prediction are variables related to the present of grasslands (land use, crops), and variables related to altitude, soil (soil type, clay and organic matter content), groundwater level and N and P emissions to surface water. The explained variance and statistical

Opportunities for ML in sustainable agriculture

Tracking and predicting emissions from animals



Published: 14 February 2022

Modelling methane emissions from pig manure using statistical and machine learning methods

Jayanta Kumar Basak, Elanchezhian Arulmozhi, Byeong Eun Moon, Anil Bhujel & Hyeon Tae Kim

Air Quality, Atmosphere & Health **15**, 575–589 (2022) | Cite this article

Conclusion

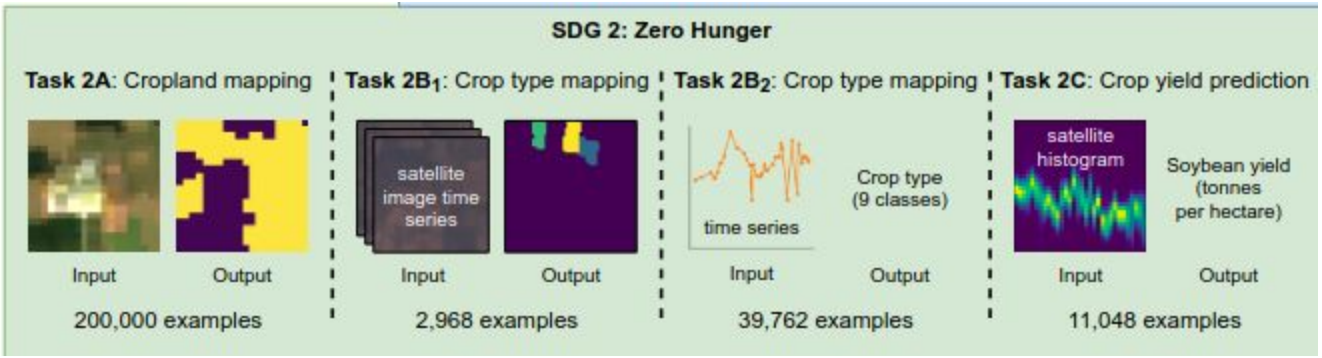
Measurements were carried out in three experimental pig's barns with three different types of concentrated diets to characterize manure production. The quantity of manure produced per pig, moisture content, DM, ash, and VS contents increased with the mass and feed intake of pigs. Body mass ranged from 60 to 90 kg a pig produced around 3.35 kg of manure per day consisting of 66% moisture content and 34% DM. The manure's ash content was 28% DM (0.47 kg pig^{-1} day^{-1}), while the VS was 72% DM (1.15 kg pig^{-1} day^{-1}). In the present study, the pigs' mass and the quantity of feed intake were used as explanatory variables to model the CH_4 production rate. Five statistical and ML algorithms were evaluated based on three statistical qualitative parameters for CH_4 emission modelling. The results showed that the regression-based models performed better than the ANN model. Moreover, the RR model was selected as the best model among those models in predicting CH_4 production. This priority for

Opportunities for ML in sustainable agriculture

Monitoring crops in order to increase yield and estimate emissions.

SustainBench: Benchmarks for Monitoring the Sustainable Development Goals with Machine Learning

Christopher Yeh* Caltech
Chenlin Meng* Stanford
Sherrie Wang* UC Berkeley
Anne Driscoll† Stanford
Erik Rozi† Stanford
Patrick Liu† Stanford
Jihyeon Lee† Stanford
Marshall Burke Stanford
David Lobell Stanford
Stefano Ermon Stanford



Opportunities for ML in sustainable agriculture

Precision agriculture

“We propose a path towards more sustainable agriculture, considering plant development an optimization problem with respect to certain parameters, such as yield and environmental impact, which can be optimized in an automated way. Specifically, we propose to use reinforcement learning to autonomously explore and learn ways of influencing the development of certain types of plants, controlling environmental parameters, such as irrigation or nutrient supply, and receiving sensory feedback, such as camera images, humidity, and moisture measurements. The trained system will thus be able to provide instructions for optimal treatment of a local population of plants, based on non-invasive measurements, such as imaging”

Reinforcement Learning for Sustainable Agriculture

Jonathan Binas [1] **Leonie Luginbuehl** [2] **Yoshua Bengio** [1]

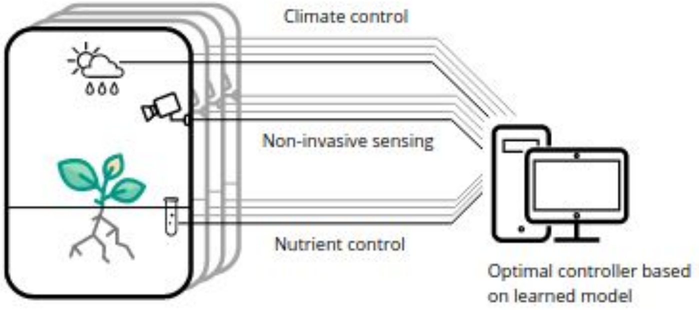


Figure 1. Illustration of the approach. After training in a controlled environment, the learned model can be used to provide optimal treatment recommendations in the field.

Opportunities for ML in sustainable agriculture

In general, approaches that increase efficiency on farms may help reduce emissions (but may not!)

Open Access Review

Machine Learning in Agriculture: A Review

by Konstantinos G. Liakos [1], Patrizia Busato [2], Dimitrios Moshou [1,3], Simon Pearson [4] and Dionysis Bochtis [1,*]

[1] Institute for Bio-Economy and Agri-Technology (IBO), Centre of Research and Technology—Hellas (CERTH), 6th km Charilaou-Thermi Rd, GR 57001 Thessaloniki, Greece

[2] Department of Agriculture, Forestry and Food Sciences (DISAFA), Faculty of Agriculture, University of Turin, Largo Braccini 2, 10095 Grugliasco, Italy

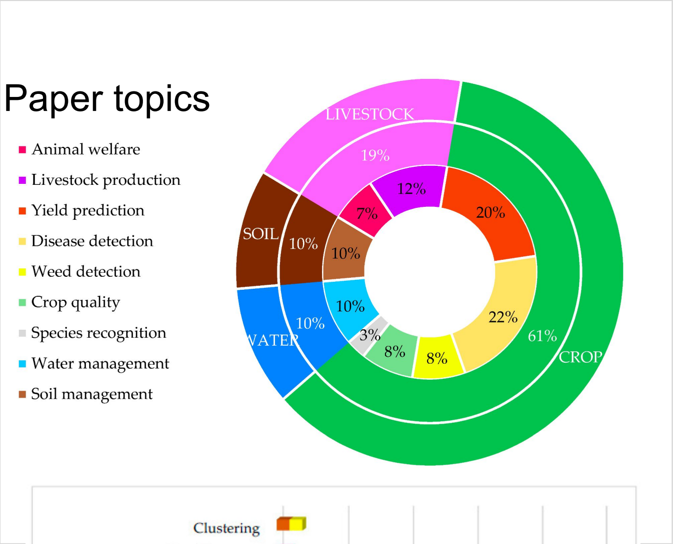
[3] Agricultural Engineering Laboratory, Faculty of Agriculture, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece

[4] Lincoln Institute for Agri-food Technology (LIAT), University of Lincoln, Brayford Way, Brayford Pool, Lincoln LN6 7TS, UK

[*] Author to whom correspondence should be addressed.

Sensors **2018**, *18*(8), 2674; **https://doi.org/10.3390/s18082674**

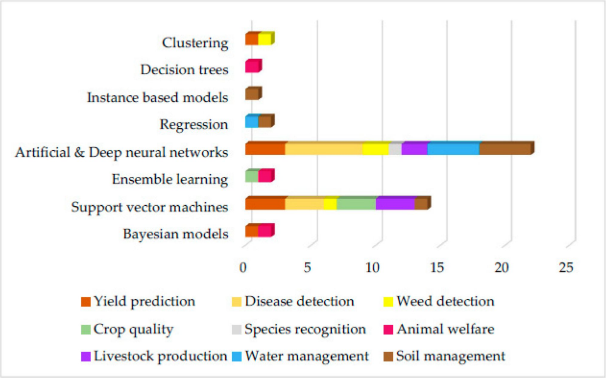
Received: 27 June 2018 / Revised: 31 July 2018 / Accepted: 7 August 2018 / Published: 14 August 2018



Abstract

Machine learning has emerged with big data technologies and high-performance computing to create new opportunities for data intensive science in the multi-disciplinary agri-technologies domain. In this paper, we present a comprehensive review of research dedicated to applications of machine learning in agricultural production systems. The works analyzed were categorized in (a) crop management, including applications on yield prediction, disease detection, weed detection crop quality, and species recognition; (b) livestock management, including applications on animal welfare and livestock production; (c) water management; and (d) soil management. The filtering and classification of the presented articles demonstrate how agriculture will benefit from machine learning technologies. By applying machine learning to sensor data, farm management systems are evolving into real time artificial intelligence enabled programs that provide rich recommendations and insights for farmer decision support and action.

Keywords: crop management; water management; soil management; livestock management; artificial intelligence; planning; precision agriculture



Paper Deep Dive

Open Access Article

Predicting and Mapping of Soil Organic Carbon Using Machine Learning Algorithms in Northern Iran

by Mostafa Emadi [1], Ruhollah Taghizadeh-Mehrjardi [2,3], Ali Cherati [4], Majid Danesh [1], Amir Mosavi [5,6,7,*] and Thomas Scholten [2,8,9]

1 Department of Soil Science, College of Crop Sciences, Sari Agricultural Sciences and Natural Resources University, Sari 4818168984, Iran
2 Department of Geosciences, Soil Science and Geomorphology, University of Tübingen, 72070 Tübingen, Germany
3 Faculty of Agriculture and Natural Resources, Ardakan University, Ardakan 8951656767, Iran
4 Soil and Water Research Department, Mazandaran Agricultural and Natural Resources Research and Education Center, AREEO, Sari 4849155356, Iran
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Remote Sens. **2020**, *12*(14), 2234; **https://doi.org/10.3390/rs12142234**

Received: 21 May 2020 / Revised: 6 July 2020 / Accepted: 9 July 2020 / Published: 12 July 2020

https://www.mdpi.com/2072-4292/12/14/2234

Goal: Predict the amount carbon stored in soil based on other factors of the land that normally correlate with it.

Brainstorm

What kind of data would you want to have to be able to approach this problem?

What kind of methods would you apply?

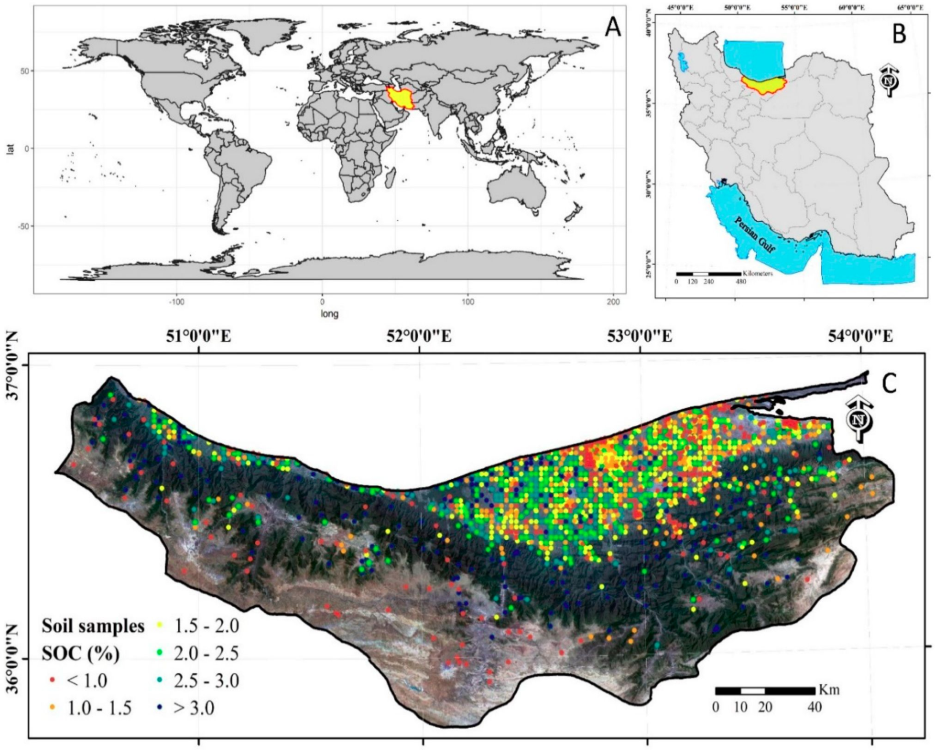
How would you measure success?

If successful, how could this system be useful?

Data: Target variable

Northern region of Iran where some on-the-ground tests of soil carbon have been made

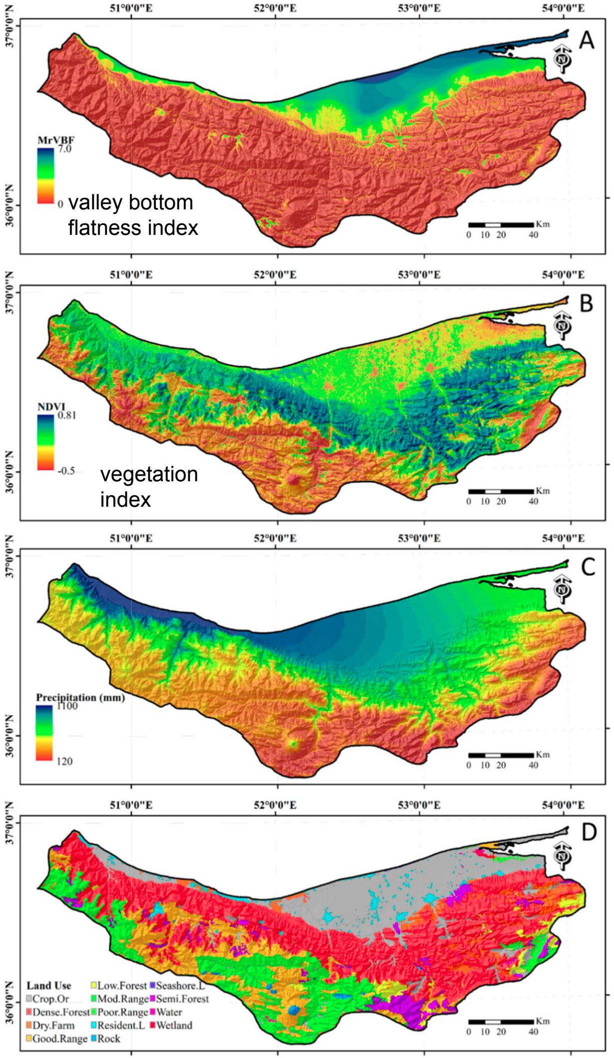
Dataset contains 1879 composite surface soil samples from two main sources (Figure 1). More than half of the data (1055 samples) were derived from five Master of Science (M.Sc.) research projects in the soil science department at Sari Agricultural Sciences and Natural Resources University (SANRU) [60,61,62,63,64]. These samples were collected using a simple random sampling scheme mostly in *uncultivated areas*. The rest of the dataset comes from soil surveys performed by the Agricultural Research Education and Extension Organization (AREEO) and the Ministry of Jahad-e-Keshvarzi in Sari, Northern Iran. These samples were mostly collected in *cultivated areas* spread across the province using a grid sampling scheme with a 2000 m grid interval.



Data: Predictors

The authors collected a wide range of data that could be predictive of soil carbon.

Regressors included variables derived from remotely sensed imagery (60 variables from Landsat 8 and MODerate-resolution Imaging Spectroradiometer, MODIS), terrain attributes (30 variables), climatic data (10 variables), and five categorical data (e.g., soil map and land use map).



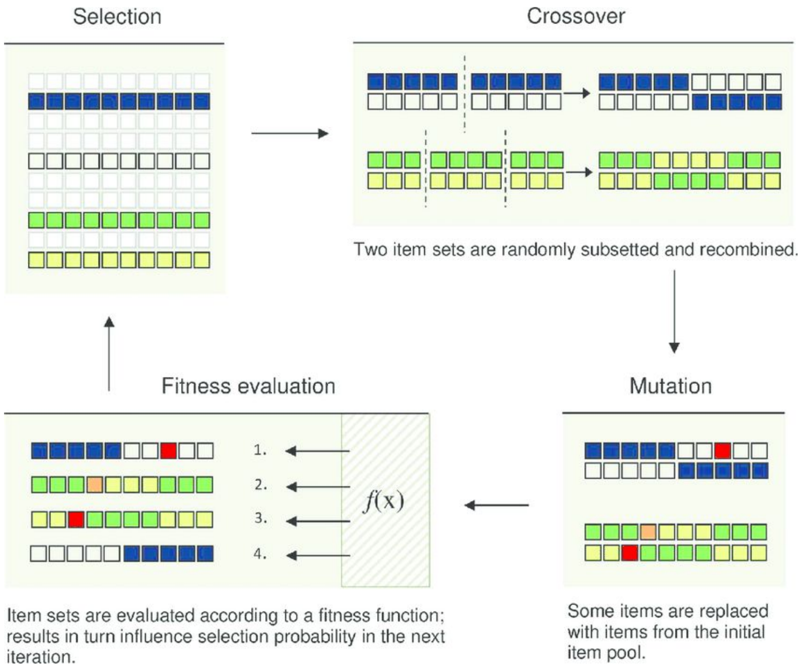
Methods: Feature selection

Genetic algorithm is used to pare down the list of predictors.

2.4. Selection of Auxiliary Variables Using Genetic Algorithms (GA)

Instead of taking all 105 environmental auxiliary variables into consideration for a predictive ML algorithm, the feature selection method reduces the number and collinearity of the auxiliary variables. The most informative auxiliary variables should be inserted into the algorithms with the aim of high accuracy of the ML algorithms for SOC prediction [9,16,25]. The selection of the significant environment auxiliary variables is a preprocessing step for ML algorithms to remove redundant and irrelevant variables. For this study, one of the most advanced algorithms for feature selection, namely the genetic algorithm (GA), was used to select the most appropriate auxiliary data to be fed as inputs to the ML algorithms [16]. GA is able to select those auxiliary data that are not only essential but improve performance as well. Moreover, GA can manage the nonlinear relationships between SOC and auxiliary data [70].

By mimicking natural biological evolution, the GA which is a heuristic search algorithm provides the best value for a function [51]. A GA feature selection process starts with an initial random population consisting of individuals. The individuals, representing subsets of auxiliary data, are encoded as binary in which 1 represents if the feature is selected and 0 otherwise [71]. Then three primary operations including selection, crossover, mutation repeat until a stopping criterion is reached. The selection operations were for selecting the two fittest individuals for reproduction (i.e., the solutions providing the lowest root mean squared error, RMSE). The crossover recombines two individuals to create new ones which may be better. The mutation operator introduces alteration in a small number of individuals. The process of selection, crossover, and mutation continues until a termination condition is satisfied [48,52]. Importantly, for each generation, it is necessary to assign a fitness value to each individual in the population so that the RMSE values are calculated by fitting the random forest model [46,48,52].



Schroeders et al, 2016

Methods: Feature selection

GA selected 35 predictors out of 105 environmental variables.

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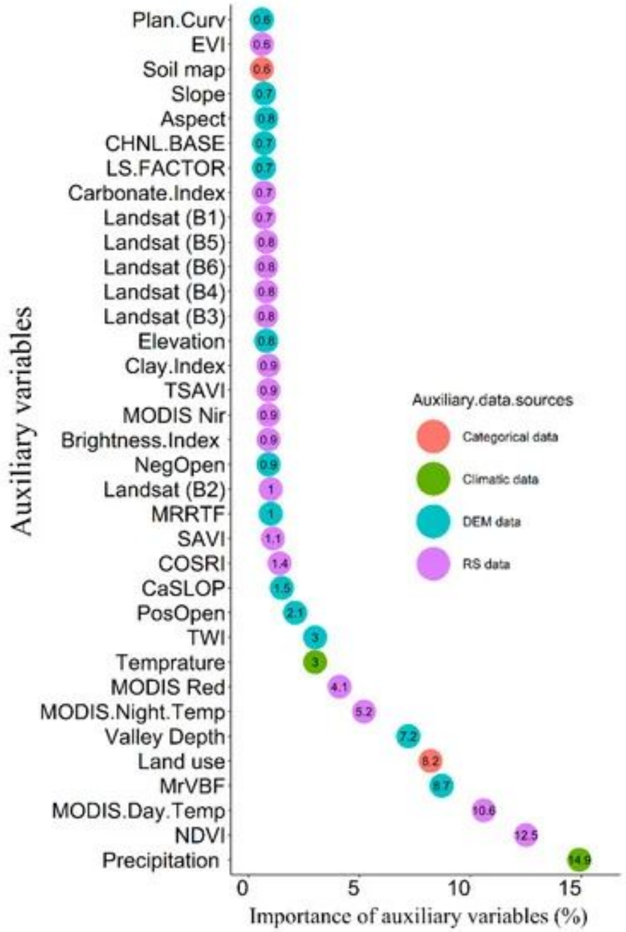


Methods: Models

The study compares a variety of regression techniques:

support vector machines (SVM), artificial neural networks (ANN), regression tree, random forest (RF), extreme gradient boosting (XGBoost), and conventional deep neural network (DNN)

Evaluation

R^2

Lin's concordance correlation coefficient

Mean absolute error

Root mean square error

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (Oi - p)^2}{\sum_{i=1}^{n} (Oi - O')^2} \right)$$

$$CCC = \frac{2\, r\, \sigma_o \sigma_p}{\sigma_o^2 + \sigma_p^2 + [O' - P']^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Pi - Oi|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Pi - Oi)^2}$$

Results

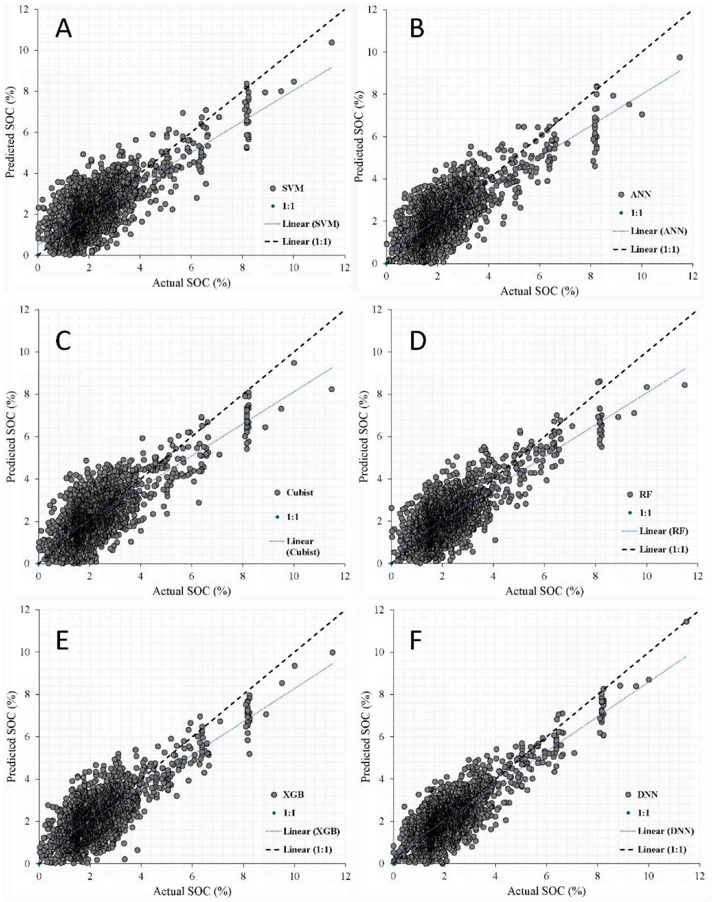
Results

Table 4. Comparisons of the accuracy of six machine learning models for validation dataset by 10-fold cross-validation (means ± standard deviation).

ML Algorithms	MAE	RMSE	R^2	CCC
SVM	0.69 ± 0.07	0.87 ± 0.05	0.53 ± 0.05	0.76 ± 0.05
ANN	0.67 ± 0.08	0.85 ± 0.07	0.55 ± 0.05	0.77 ± 0.06
Cubist	0.66 ± 0.06	0.83 ± 0.04	0.57 ± 0.04	0.78 ± 0.04
RF	0.65 ± 0.03	0.82 ± 0.03	0.58 ± 0.05	0.78 ± 0.03
XGB	0.66 ± 0.04	0.83 ± 0.04	0.57 ± 0.03	0.78 ± 0.04
DNN	0.59 ± 0.06	0.75 ± 0.06	0.65 ± 0.05	0.83 ± 0.06

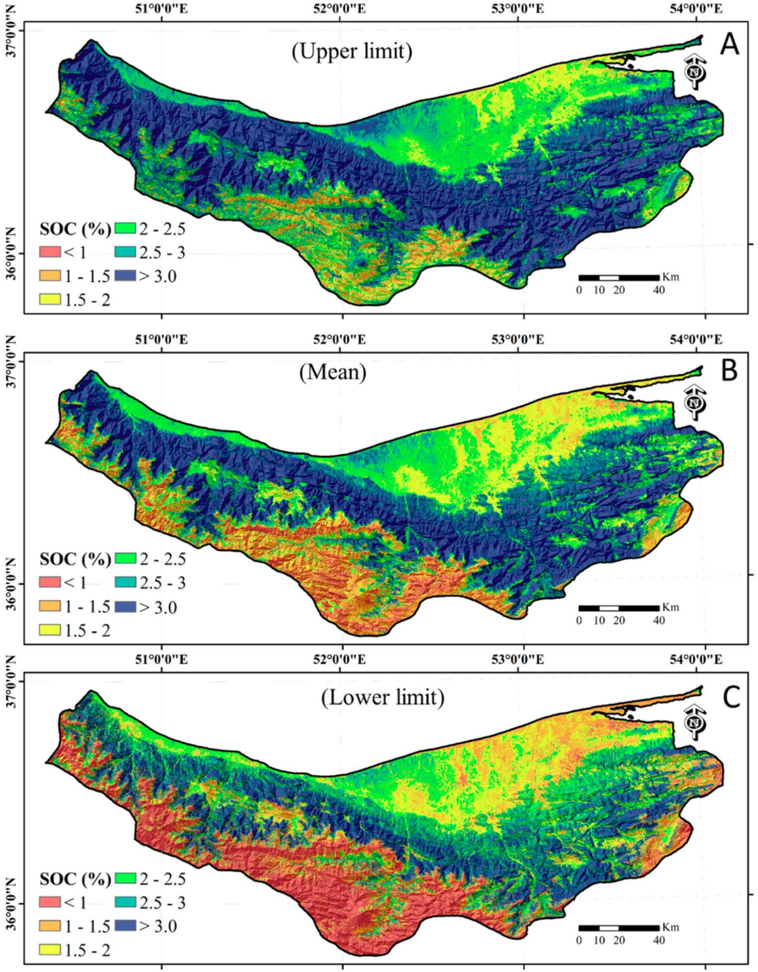
ML: machine learning; SVM: support vector machine; Cubist: regression tree; XGBoost: an extreme gradient boosting; RF: random forest; ANN: artificial neural networks; DNN: deep neural networks; MAE: mean absolute error; RMSE: root mean square error; R^2: the coefficient of determination; CCC: Lin's concordance correlation coefficient.

The DNN model outperforms other models by delivering 65% of the SOC variability. The DNN algorithm showed the lowest mean MAE value (0.59) of the six studied ML algorithms. The DNN outperformed with the lowest mean RMSE value (0.75).



Application of the model

"The predicted SOC map could be used as a base-line for further studies and projects related to the C sequestration development both locally in soils of the Mazandaran province and globally at the worldwide scale."



Further Resources

Overviews of emissions from agriculture:

https://www.wri.org/insights/everything-you-need-know-about-agricultural-emissions

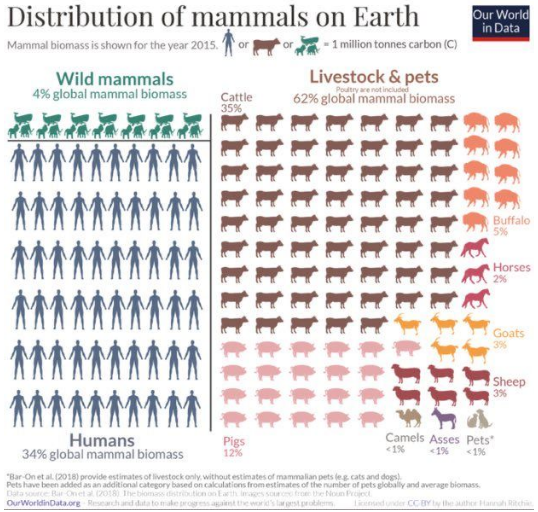
https://ourworldindata.org/environmental-impacts-of-food

IPCC recommendations for the food system:
https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-on-how-to-tackle-climate-change/ (item 6)

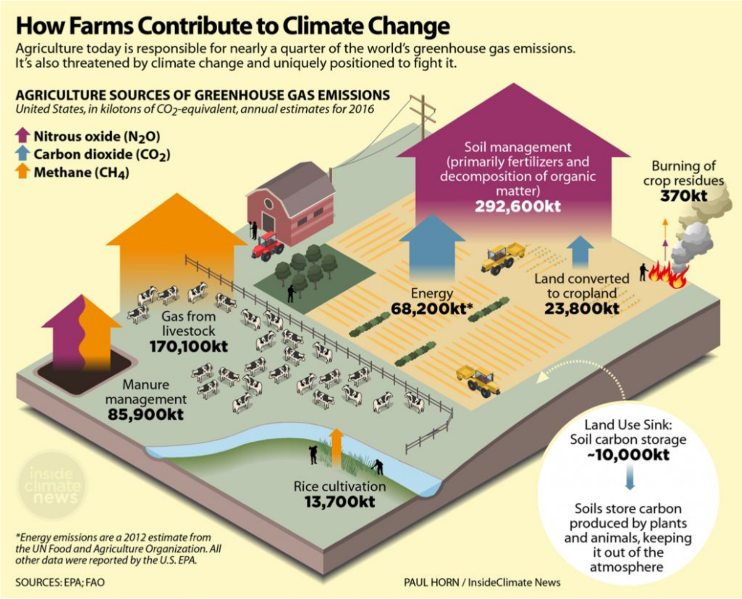
Scientific review of GHG sources and opportunities for change in food production and consumption https://www.science.org/doi/full/10.1126/science.aaq0216

“Future cookbook” article:
https://grist.org/fix/food-farming/climate-cookbook-sustainable-recipes/

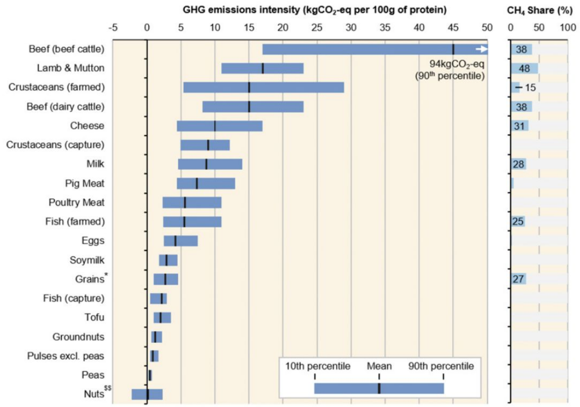
Summary



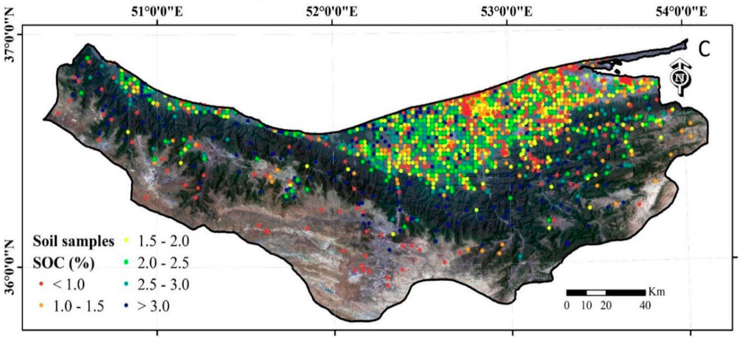
Distribution of mammals on Earth
Our World in Data
Mammal biomass is shown for the year 2015. or or = 1 million tonnes carbon (C)
Wild mammals
4% global mammal biomass
Livestock & pets
Poultry are not included
62% global mammal biomass
Cattle
35%
Buffalo
5%
Horses
2%
Goats
3%
Sheep
3%
Pigs
12%
Camels
<1%
Asses
<1%
Pets*
<1%
Humans
34% global mammal biomass
*Bar-On et al. (2018) provide estimates of livestock only, without estimates of mammalian pets (e.g. cats and dogs).
Pets have been added as an additional category based on calculations from estimates of the number of pets globally and average biomass.
OurWorldinData.org – Research and data to make progress against the world's largest problems.



How Farms Contribute to Climate Change
Agriculture today is responsible for nearly a quarter of the world's greenhouse gas emissions.
It's also threatened by climate change and uniquely positioned to fight it.
AGRICULTURE SOURCES OF GREENHOUSE GAS EMISSIONS
United States, in kilotons of CO_2-equivalent, annual estimates for 2016
Nitrous oxide (N_2O)
Carbon dioxide (CO_2)
Methane (CH_4)
Soil management (primarily fertilizers and decomposition of organic matter)
292,600kt
Burning of crop residues
370kt
Energy
68,200kt*
Land converted to cropland
23,800kt
Gas from livestock
170,100kt
Manure management
85,900kt
Rice cultivation
13,700kt
Land Use Sink: Soil carbon storage
~10,000kt
Soils store carbon produced by plants and animals, keeping it out of the atmosphere
*Energy emissions are a 2012 estimate from the UN Food and Agriculture Organization. All other data were reported by the U.S. EPA.
SOURCES: EPA; FAO
PAUL HORN / InsideClimate News



GHG emissions intensity ($kgCO_2$-eq per 100g of protein)
CH_4 Share (%)
-5 0 5 10 15 20 25 30 35 40 45 50
0 50 100
Beef (beef cattle)
Lamb & Mutton
Crustaceans (farmed)
Beef (dairy cattle)
Cheese
Crustaceans (capture)
Milk
Pig Meat
Poultry Meat
Fish (farmed)
Eggs
Soymilk
Grains*
Fish (capture)
Tofu
Groundnuts
Pulses excl. peas
Peas
Nuts$$
94kgCO$_2$-eq (90th percentile)
38
48
15
38
31
28
25
27
10th percentile
Mean
90th percentile



51°0'0"E
52°0'0"E
53°0'0"E
54°0'0"E
37°0'0"N
36°0'0"N
C
Soil samples
SOC (%)
< 1.0
1.0 - 1.5
1.5 - 2.0
2.0 - 2.5
2.5 - 3.0
> 3.0
Km
0 10 20 40