Food and Agriculture Emissions

Food production and waste

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

Revealed: more than 90% of rainforest carbon offsets by biggest provider are worthless, analysis shows

The investigation found that:

- Only a handful of Verra's rainforest projects showed evidence of deforestation reductions, according to two studies, with further analysis indicating that 94% of the credits had no benefit to the climate.
- The threat to forests had been overstated by about 400% on average for Verra projects, according to analysis of a 2022 University of Cambridge study.
- Gucci, Salesforce, BHP, Shell, easyJet, Leon and the band Pearl Jam were among dozens of companies and organisations that have bought rainforest offsets approved by Verra for environmental claims.

Step 1

Offsetting project set up

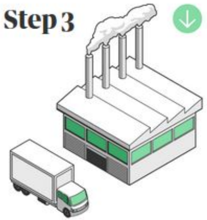
A project is established to mitigate global heating. Many are avoided-emission projects that prevent greenhouse gases from being released from deforestation or fossil fuels, but do not remove carbon from the atmosphere.

Step 2

Credits are calculated

Carbon credits are calculated using dozens of methods. Avoided-deforestation projects estimate what would happen if the project was not there. Projects claim the difference between what happens and what could have as credits.

Step 3



Company makes net zero strategy

Firms work out the emissions they are producing every year from their own activities. In order to meet their net zero strategy, alongside efforts to cut emissions, some companies decide to buy carbon offsets.

Step 4

Company searches for carbon credits

Firms get carbon credits through a specialist broker, others go directly to a project. Most offsets are approved by Verra and Gold Standard. These credits are used to offset emissions, allowing them to claim large net reductions.

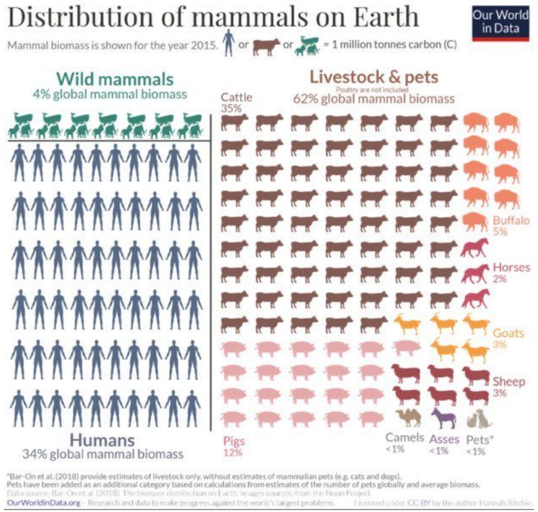
Step 5

Company makes climate claim

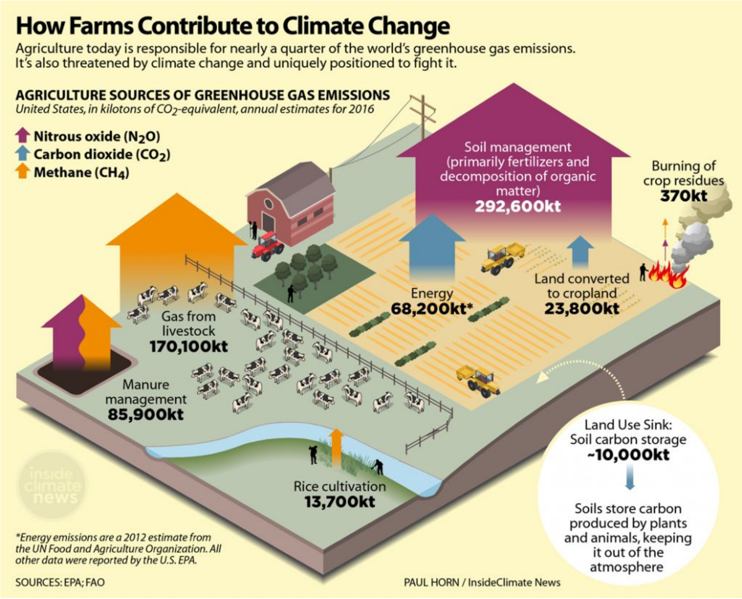
Once a firm has worked out the amount of carbon they want to offset, they buy the equivalent amount of credits. Many then claim the company or product they are selling has become carbon neutral.

Guardian graphic. Source: Guardian reporting

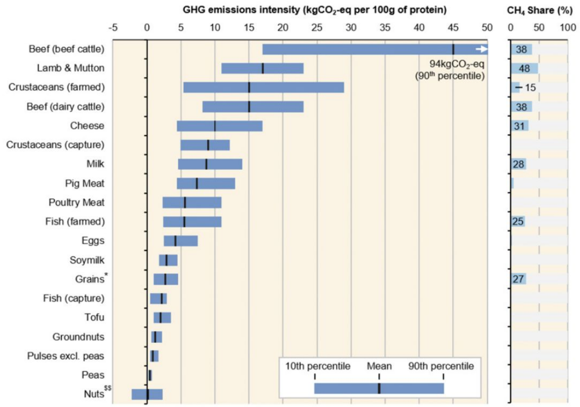
Recap



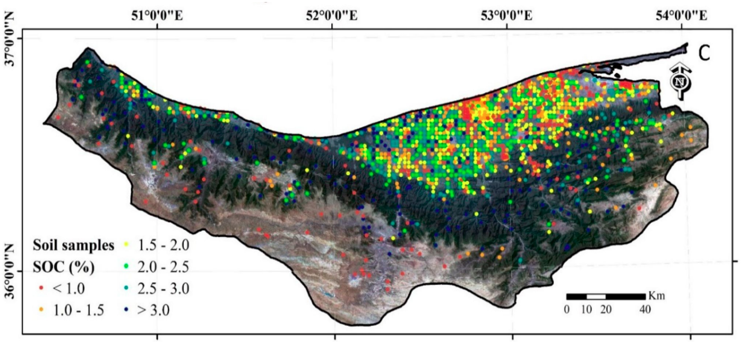
Distribution of mammals on Earth
Our World in Data
Mammal biomass is shown for the year 2015. or or = 1 million tonnes carbon (C)
Wild mammals
4% global mammal biomass
Livestock & pets
Poultry are not included
62% global mammal biomass
Cattle
35%
Buffalo
5%
Horses
2%
Goats
3%
Sheep
3%
Humans
34% global mammal biomass
Pigs
12%
Camels
<1%
Asses
<1%
Pets*
<1%
*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



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

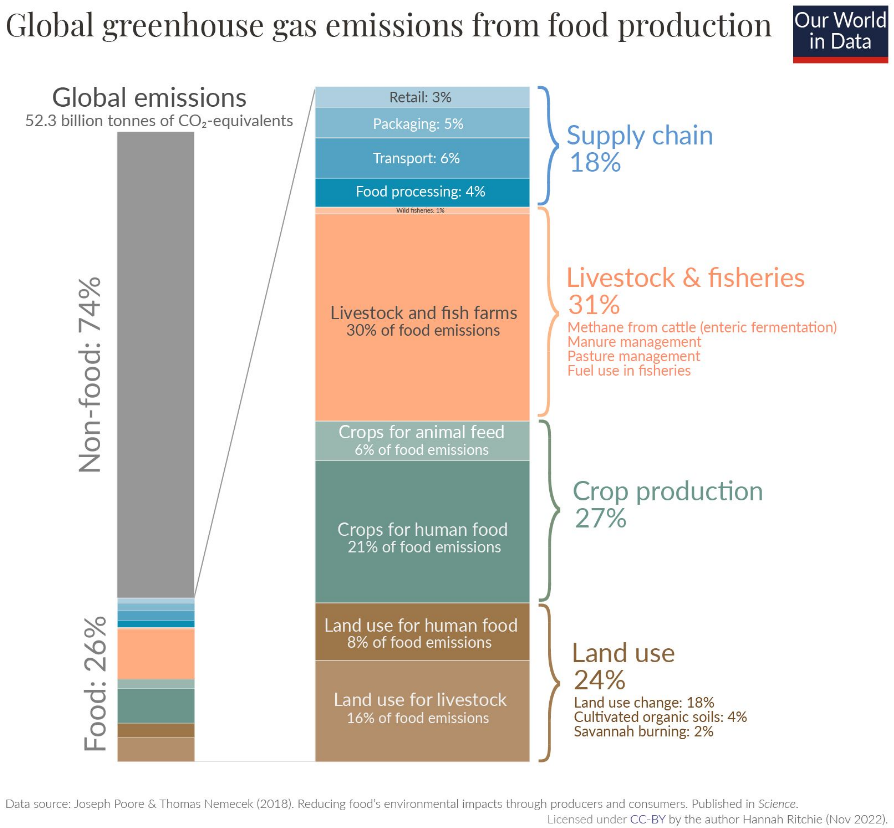


GHG emissions intensity ($kgCO_2$-eq per 100g of protein)
CH_4 Share (%)
-5 0 5 10 15 20 25 30 35 40 45 50
0 50 100
Beef (beef cattle)
Lamb & Mutton
Crustaceans (farmed)
Beef (dairy cattle)
Cheese
Crustaceans (capture)
Milk
Pig Meat
Poultry Meat
Fish (farmed)
Eggs
Soymilk
Grains*
Fish (capture)
Tofu
Groundnuts
Pulses excl. peas
Peas
Nuts$$
94kgCO2-eq
(90th percentile)
38
48
15
38
31
28
25
27
10th percentile
Mean
90th percentile



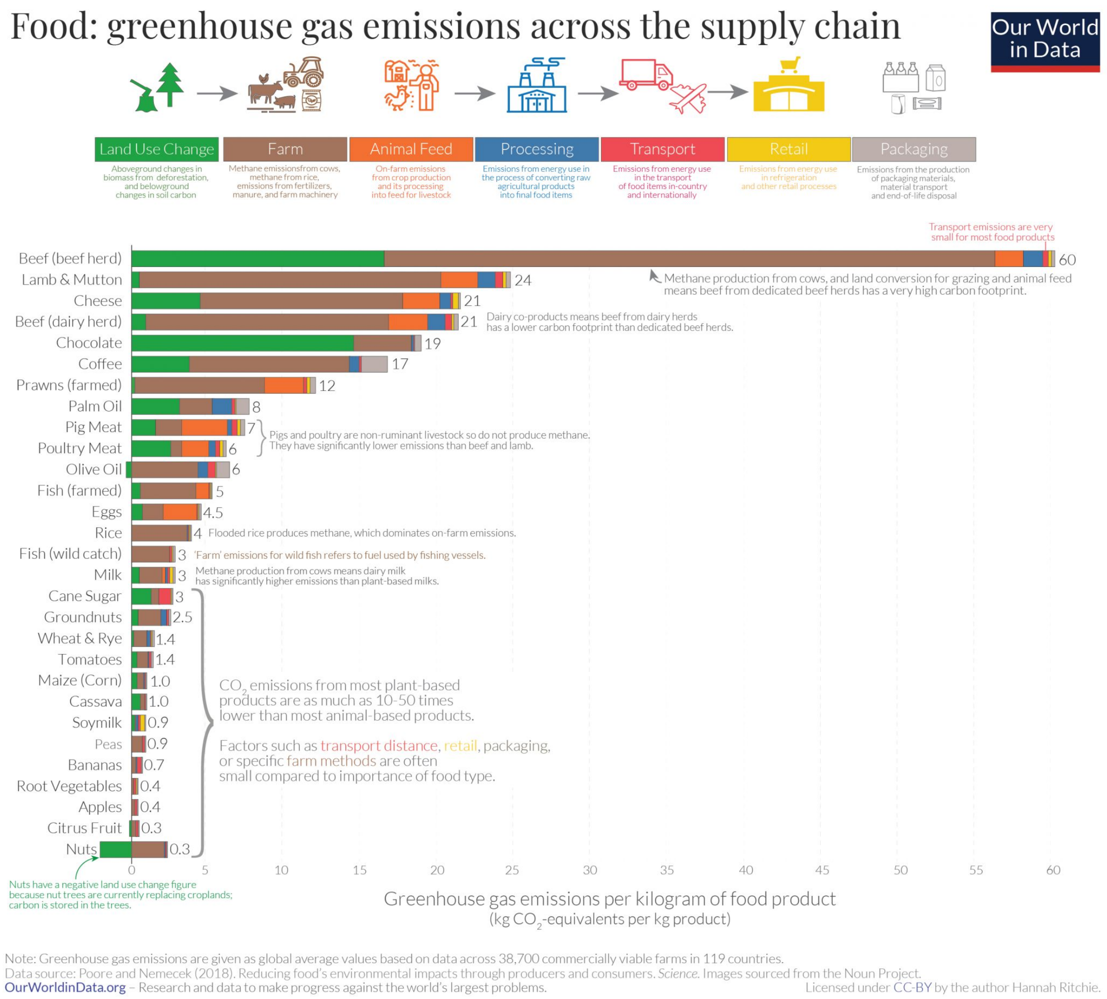
51°0'0"E
52°0'0"E
53°0'0"E
54°0'0"E
37°0'0"N
36°0'0"N
C
Soil samples
SOC (%)
< 1.0
1.0 - 1.5
1.5 - 2.0
2.0 - 2.5
2.5 - 3.0
> 3.0
Km
0 10 20 40

The majority of food emissions come from agriculture



However, sources of emissions vary by food type.

Soymilk, for example, produces emissions from different sources in roughly equal proportions.

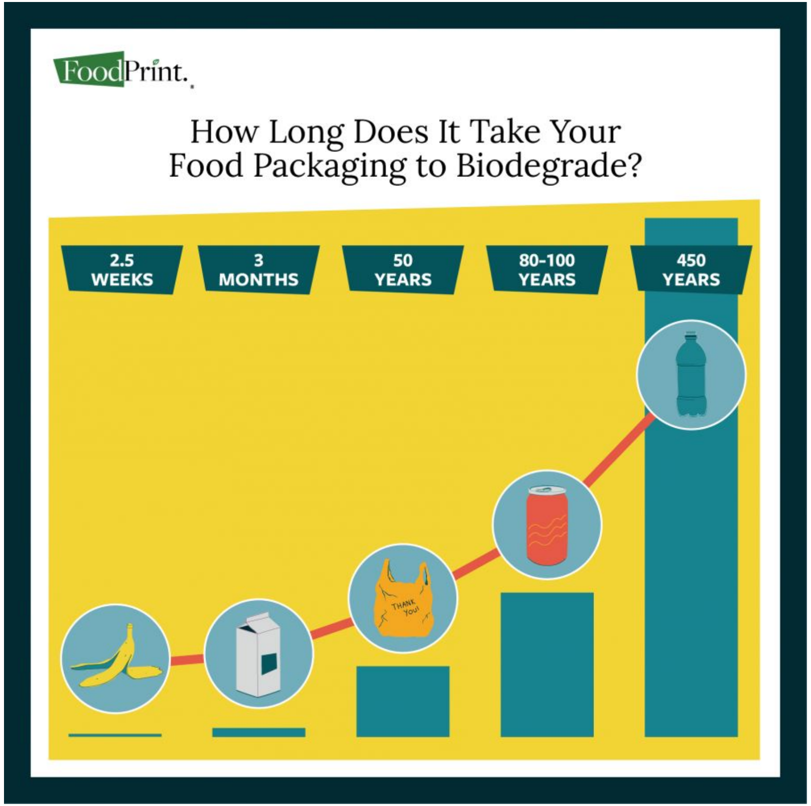


Impacts of food packaging

Each form of packaging uses a lot of resources like energy, water, chemicals, petroleum, minerals, wood and fibers to produce. Its manufacture often generates air emissions including greenhouse gases, heavy metals and particulates, as well as wastewater and/or sludge containing toxic contaminants.

In the US, the major source of feedstocks for plastics production is natural gas, derived either from natural gas processing or from crude oil refining.

Plastics manufacturing is responsible for as much as one percent of US GHG emissions. Other air emissions from plastics production include nitrous oxides, hydrofluorocarbons, perfluorocarbons and sulfur hexafluoride.

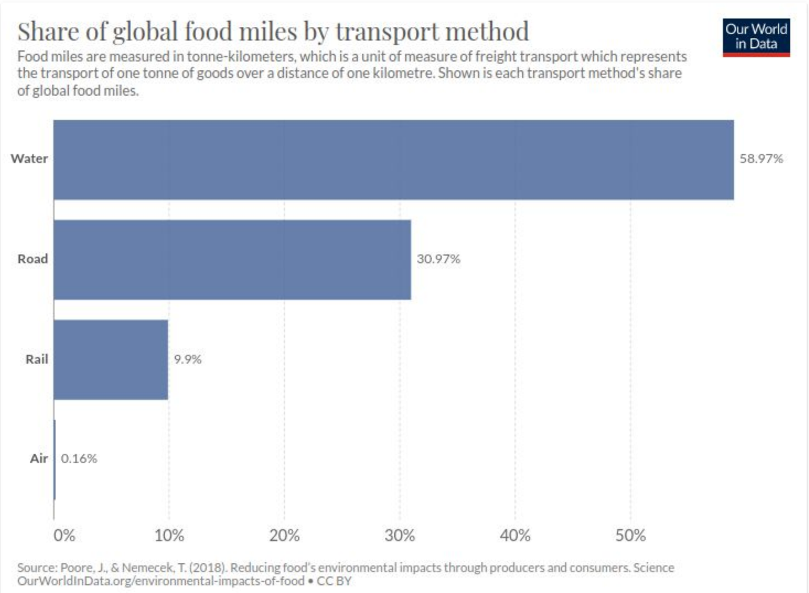


https://foodprint.org/issues/the-environmental-impact-of-food-packaging/

Food transportation

Only a small fraction of food is transported by the most emissions-heavy routes.

Foods most likely to travel by air are those that have a short shelf life and most be grown far away, such as berries.



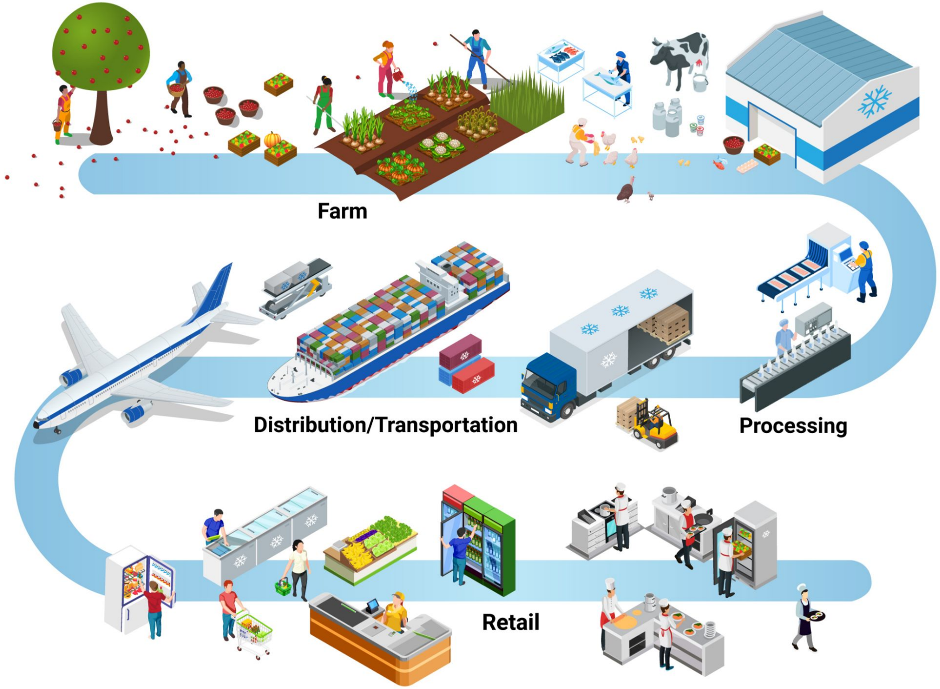
Emission factors for freight by transport mode (kilograms of CO_2eq per tonne-kilometer)[3]

Transport mode	Ambient transport (kg CO_2eq per tonne-kilometer)	Temperature-controlled transport (kg CO_2eq per tonne-kilometer)
Road Transport	0.2	0.2 to 0.66
Rail Transport	0.05	0.06
Sea / Inland Water Transport	0.01	0.02
Air Transport	1.13	1.13

https://ourworldindata.org/food-transport-by-mode

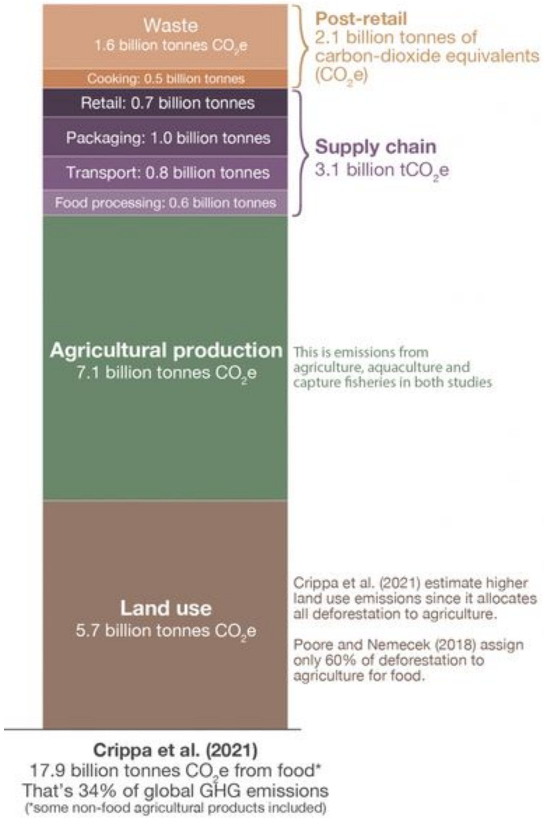
Cold chain

The majority of the gases used in refrigerants are hydrofluorocarbons, or HFCs which are hundreds to thousands of times more potent a greenhouse gas than carbon dioxide.



https://ozone.unep.org/coldchainexhibition/index.html

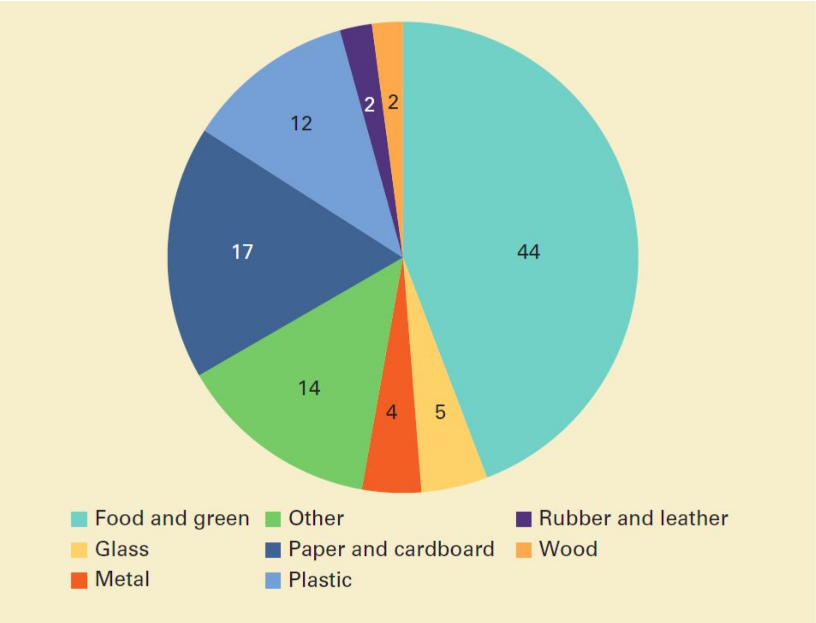
Food waste also contributes to emissions

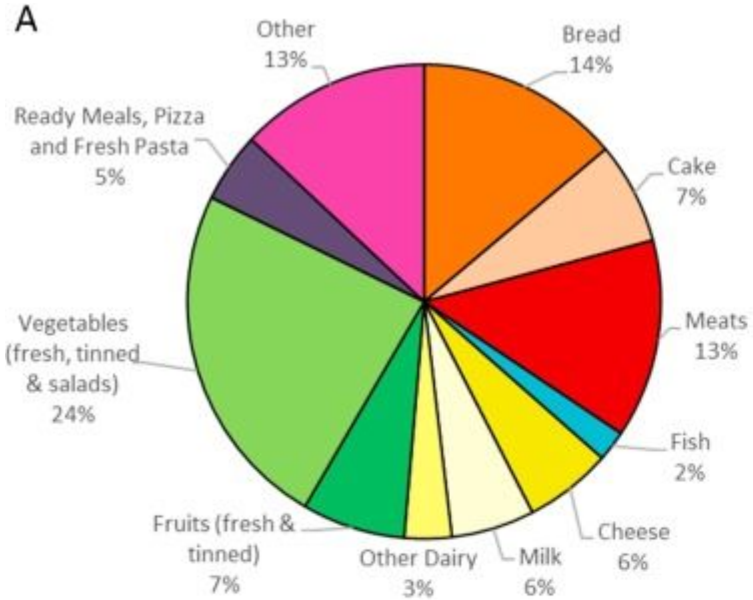


74kg (163 lbs) of food waste per person, per year.

What goes to waste

Composition of waste





Example grocery store

world bank

https://www.sciencedirect.com/science/article/pii/S0306919217309168

Where waste goes

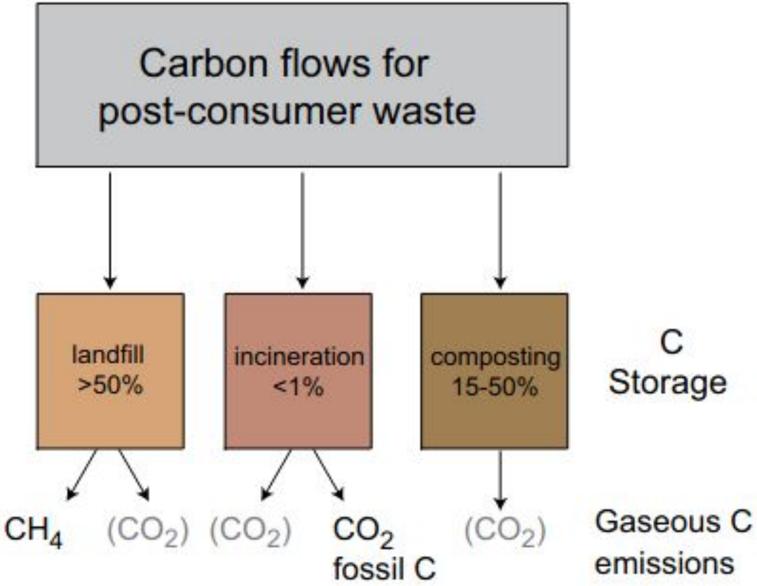
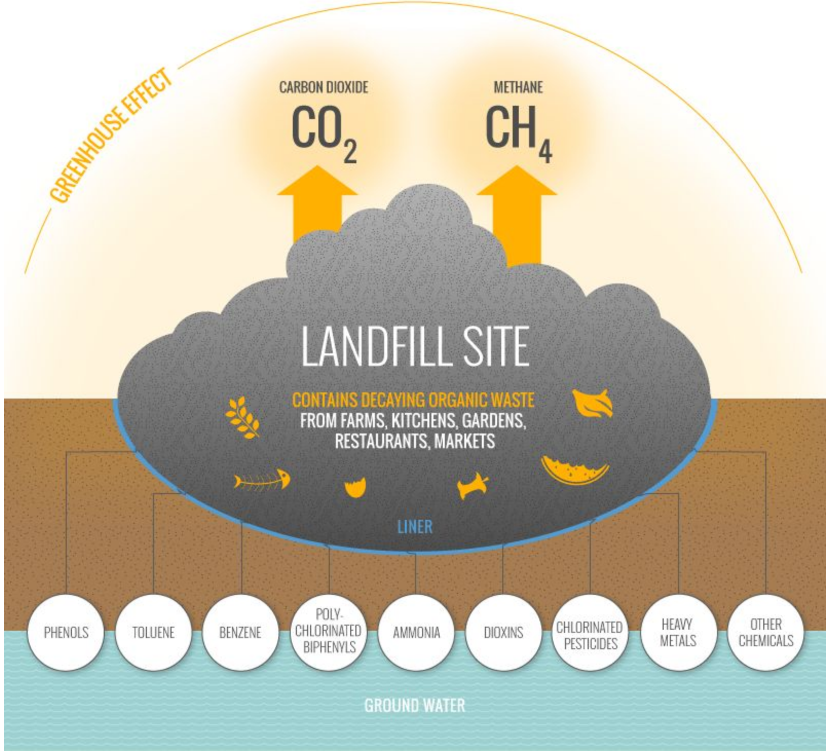


Figure 10.1: *Carbon flows through major waste management systems including C storage and gaseous C emissions. The CO_2 from biomass is not included in GHG inventories for waste.*

References for C storage are: Huber-Humer, 2004; Zinati et al., 2001; Barlaz, 1998; Bramryd, 1997; Bogner, 1992.

Landfill emissions

When organic waste decomposes, carbon dioxide (aerobic) and methane (anaerobic) gas is created.



Landfill gas is typically 50 percent methane, 50 percent carbon dioxide (CO_2) and a small amount of non-methane organic compounds.

http://gazasia.com

Compost

Food waste can be composted instead of sent to a landfill.

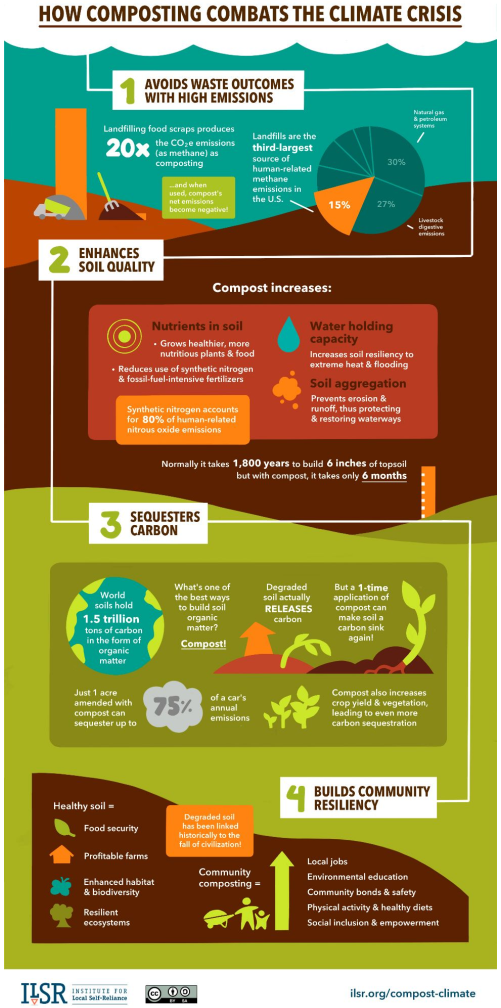
Compost

Food waste can be composted instead of sent to a landfill.

It is still not a complete replacement for artificial fertilizer due to cost and space:

“A single 40-pound bag of fertilizer costs about $20. The equivalent is about 280 pounds of compost ($35) or 800 pounds of cow manure ($96) to provide the same nutrients.”

https://newswire.caes.uga.edu/story/8896/compost-and-fertilizer.html



Waste in New York City

2:09-6:35

What needs to be done

IPCC: “Reducing food loss and waste globally has the technical potential to cut emissions globally by 2.1GtCO2e, with a range of 0.1-5.8GtCO2e, the report estimates with medium confidence.

There is high agreement that mitigating food-sector emissions to their full potential ‘requires change at all stages, from producer to consumer and waste management’ via integrated packages of policy including supply- and demand-side measures.”

What needs to be done

UN Sustainable Development Goals

The 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015, provides a shared blueprint for peace and prosperity for people and the planet, now and into the future. At its heart are the 17 Sustainable Development Goals (SDGs), which are an urgent call for action by all countries - developed and developing - in a global partnership. They recognize that ending poverty and other deprivations must go hand-in-hand with strategies that improve health and education, reduce inequality, and spur economic growth – all while tackling climate change and working to preserve our oceans and forests.

What needs to be done

UN Sustainable Development Goals aim for more productive and sustainable agriculture.

2.3 By 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists and fishers, including through secure and equal access to land, other productive resources and inputs, knowledge, financial services, markets and opportunities for value addition and non-farm employment.

2.4 By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality.

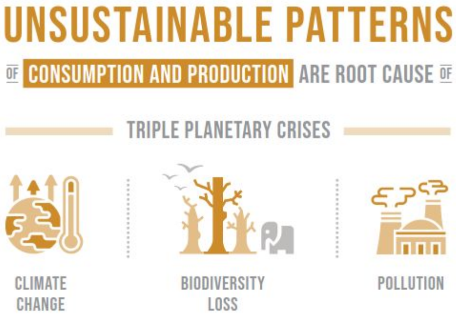
What needs to be done

UN Sustainable Development Goals aim for 50% less food waste by 2030.

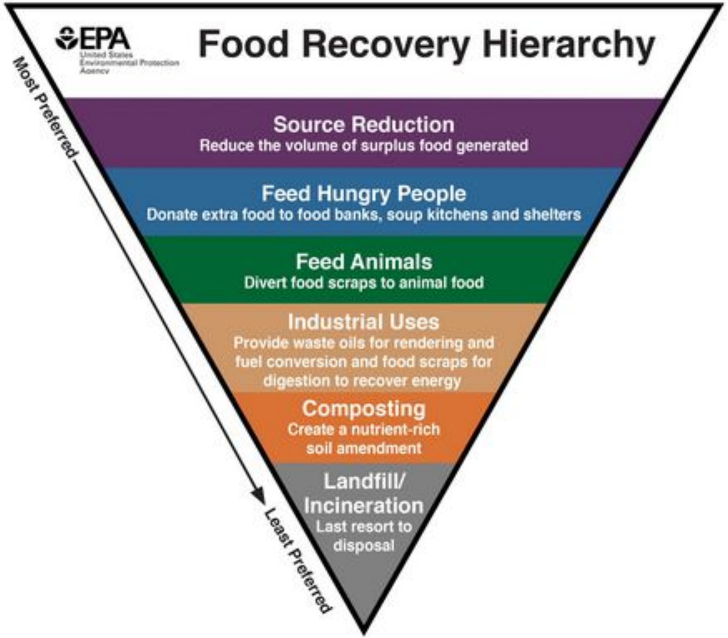
12.3 By 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses

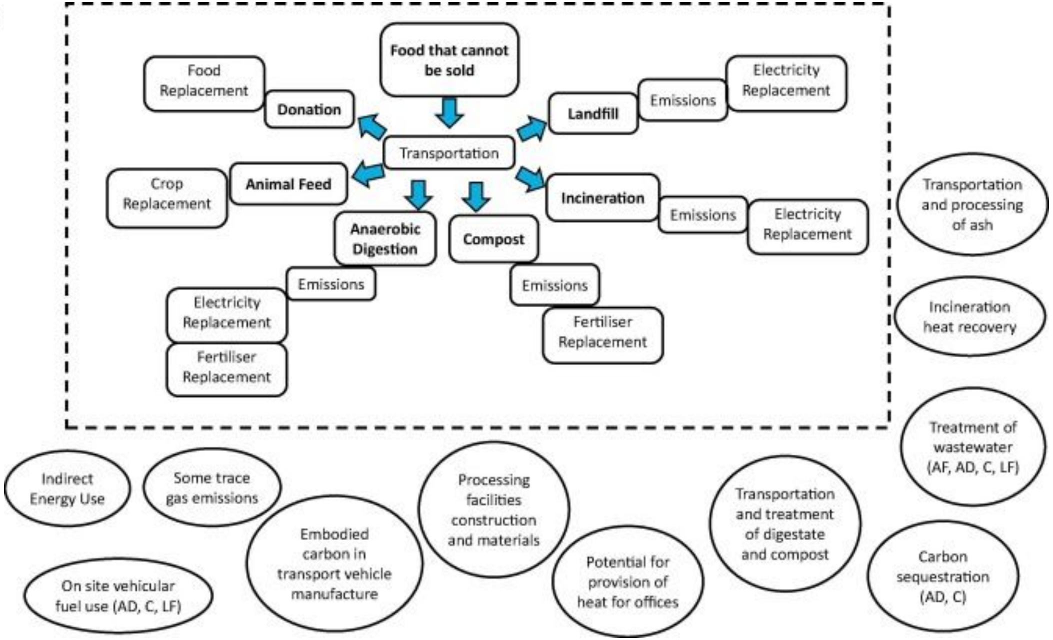
12.4 By 2020, achieve the environmentally sound management of chemicals and all wastes throughout their life cycle, in accordance with agreed international frameworks, and significantly reduce their release to air, water and soil in order to minimize their adverse impacts on human health and the environment

12.5 By 2030, substantially reduce waste generation through prevention, reduction, recycling and reuse



Food Waste Solutions





https://www.sciencedirect.com/science/article/pii/S0306919217309168

Too Good to Go

Too Good To Go

DISCOVER
delicious surplus food at a great discount around you

PICK-UP
delicious food from shops nearby

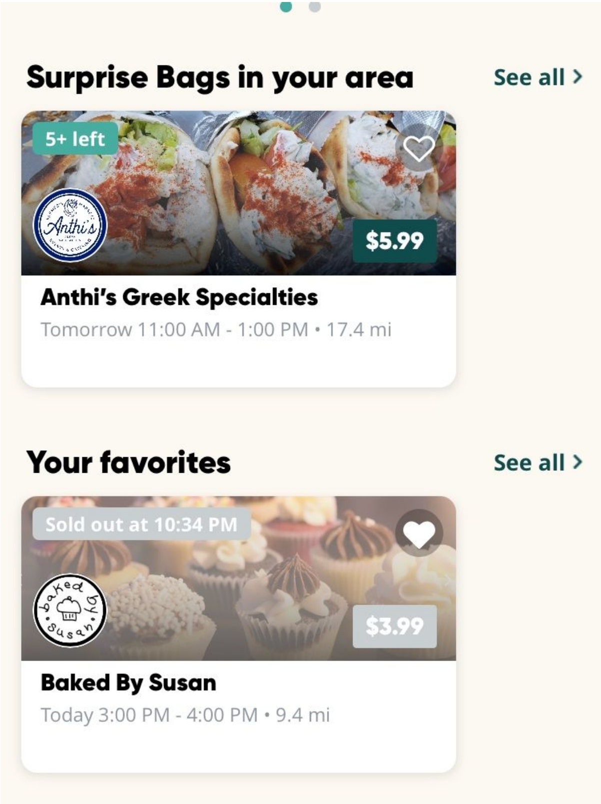
ENJOY
a tasty meal that helps the planet

WHY IT MATTERS

Globally, more than ⅓ of food is wasted - and that's bad news for our planet. Food waste is responsible for 10% of greenhouse gases, and we use a landmass the size of China to produce food we end up throwing away. It makes no sense, does it?

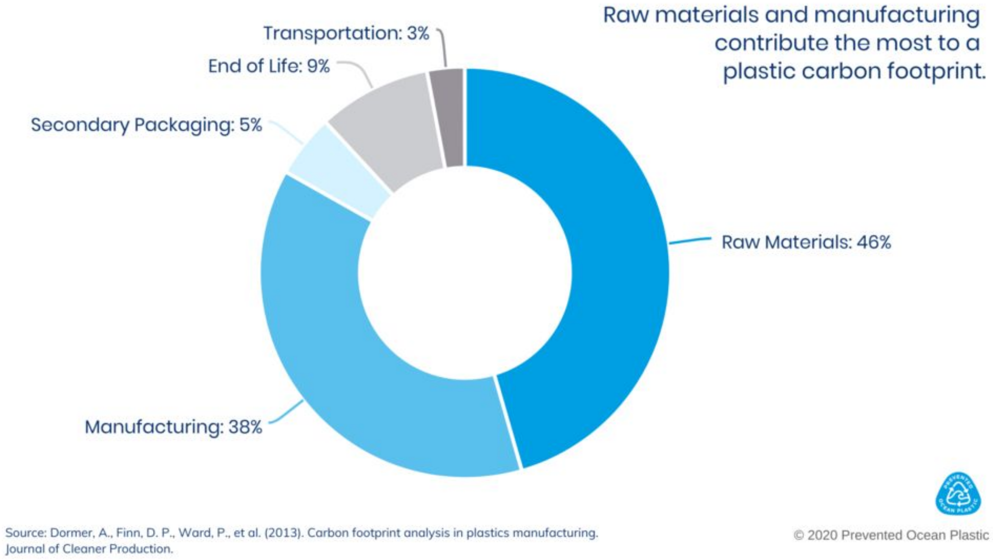
At Too Good To Go, we're determined to help fix the problem. Our app lets you rescue delicious, unsold food from businesses to save it from being thrown away.

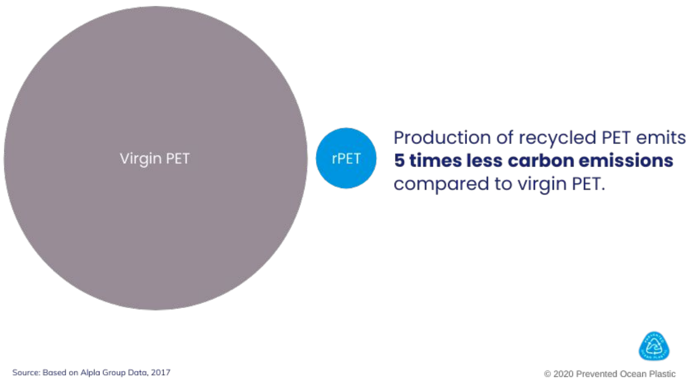
In turn, the app powers our efforts to build an anti-food waste movement. Globally, our dedicated team works within organizations like local governments and schools to shake up the food system, and change the way we think about food.



Food Packaging Solutions

Because raw material extraction is responsible for the majority of plastic's carbon emissions, recycling is far less emissions intensive than producing new plastic





Opportunities for ML in reducing food emissions

Opportunities for ML in reducing food emissions

Cold chain logistics


Trends in Food Science & Technology
Volume 112, June 2021, Pages 391-399

Cold chain break detection and analysis: Can machine learning help?

Julie Loisel [a b], Steven Duret [b], Antoine Cornuéjols [a], Dominique Cagnon [c], Margot Tardet [c], Evelyne Derens-Bertheau [b], Onrawee Laguerre [b]

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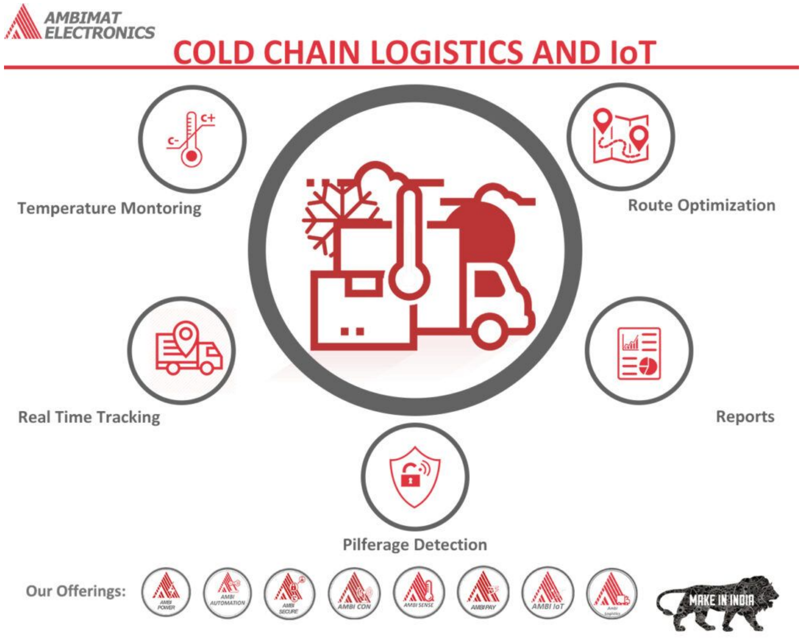
Highlights

- This article reviews cold chain break studies, conducted both on field and in laboratory.
- Machine Learning models applied to temperature prediction issues are reviewed.
- Data sources available to train machine learning models are described.



Opportunities for ML in reducing food emissions

Increasing warehouse efficiency with robotics

At Ocado, machine learning determines the traffic flow of the robots through the warehouse to prevent collisions and to optimize efforts, calculates the precise placement of bins for maximum efficiency, and also monitors the health and maintenance needs of the robots to reduce any downtime.

Artificial intelligence and machine learning also help reduce food waste by ensuring that products are stored or delivered in a way and at temperatures that reduce the likelihood of spoilage.

Opportunities for ML in reducing food emissions

Matching supply and demand

Technical Note

A systematic literature review on machine learning applications for sustainable agriculture supply chain performance

Rohit Sharma [a 1], Sachin S. Kamble [b 2], Angappa Gunasekaran [c 3], Vikas Kumar [d 4], Anil Kumar [e 5]

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Fig. 5. Journal-wise publications.

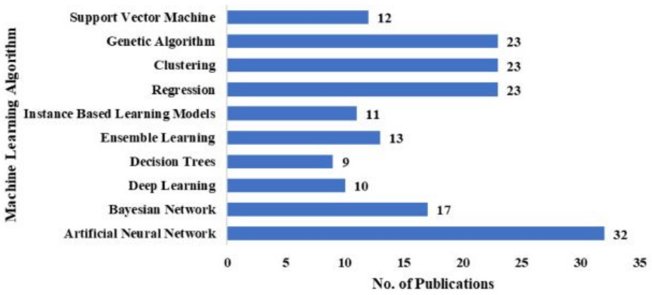

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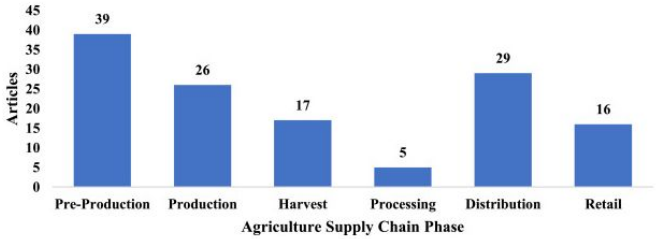
Fig. 6. Classification based on ML algorithm.



Machine Learning in Predicting Demand for Fast-Moving Consumer Goods: An Exploratory Research

Elcio Tarallo *, Getúlio K. Akabane **, Camilo I. Shimabukuro ***, Jose Mello ****, Douglas Amancio *****

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https://doi.org/10.1016/j.ifacol.2019.11.203

Reducing fresh fish waste while ensuring availability: Demand forecast using censored data and machine learning

Vera Lucia Miguéis, André Pereira, João Pereira, Gonçalo Figueira

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Articles

Machine learning demand forecasting and supply chain performance

Javad Feizabadi

Pages 119-142 | Received 19 Apr 2020, Accepted 26 Jul 2020, Published online: 04 Aug 2020

Download citation

https://doi.org/10.1080/13675567.2020.1803246

Check for updates

Opportunities for ML in reducing food emissions

Quality control in the supply chain

A critical review on computer vision and artificial intelligence in food industry

Vijay Kakani [a], Van Huan Nguyen [b], Basivi Praveen Kumar [c], Hakil Kim [a], Visweswara Rao Pasupuleti [d e]

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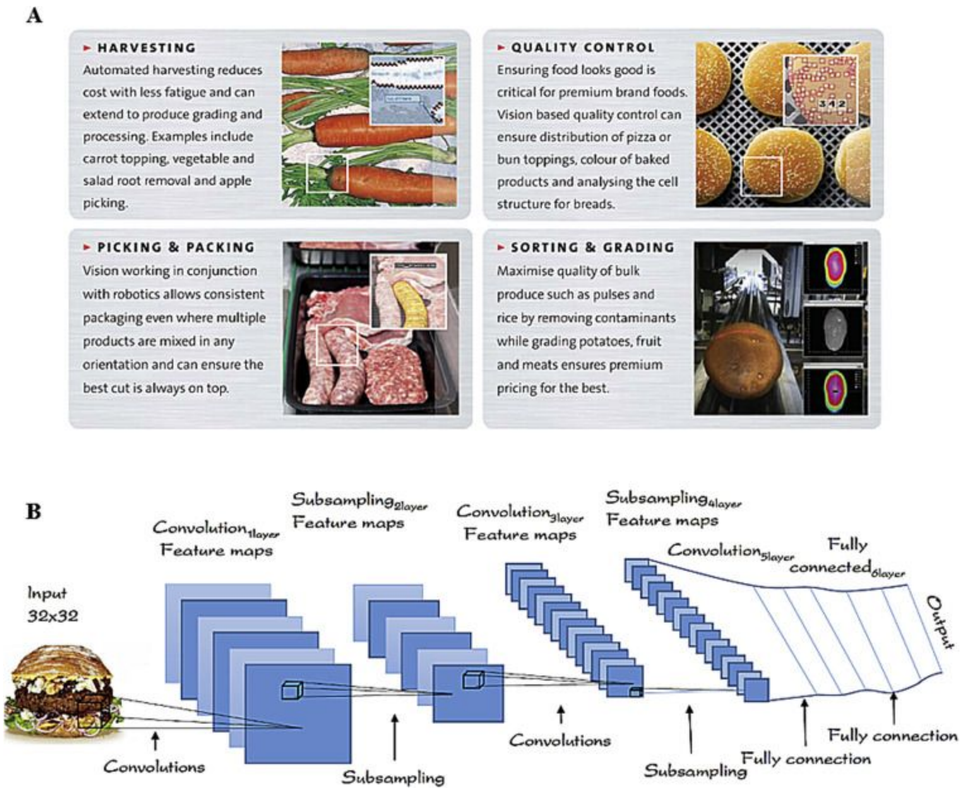
Highlights

- Food demand and sustainability to feed the growing population are explained clearly.
- The technological innovations including 4.0 industry revolution strengthen the agricultural sector.
- The usage of computer vision and artificial intelligence in the field of agriculture and food industry is deeply elaborated.



Paper Deep Dive

PHILOSOPHICAL TRANSACTIONS OF THE ROYAL SOCIETY A | MATHEMATICAL, PHYSICAL & ENGINEERING SCIENCES

Improvement in fresh fruit and vegetable logistics quality: berry logistics field studies

M. Cecilia do Nascimento Nunes, Mike Nicometo, Jean Pierre Emond, Ricardo Badia Melis and Ismail Uysal

Phil. Trans. R. Soc. A 2014 **372**, 20130307, published 5 May 2014

Shelf life of fresh fruits and vegetables is greatly influenced by environmental conditions. Increasing temperature usually results in accelerated loss of quality and shelf-life reduction, which is not physically visible until too late in the supply chain to adjust logistics to match shelf life. A blackberry study showed that temperatures inside pallets varied significantly and 57% of the berries arriving at the packinghouse did not have enough remaining shelf life for the longest supply routes. Yet, the advanced shelf-life loss was not physically visible. Some of those pallets would be sent on longer supply routes than necessary, creating avoidable waste. Other studies showed that variable pre-cooling at the centre of pallets resulted in physically invisible uneven shelf life. We have shown that using simple temperature measurements much waste can be avoided using 'first expiring first out'. Results from our studies showed that shelf-life prediction should not be based on a single quality factor as, depending on the temperature history, the quality attribute that limits shelf life may vary. Finally, methods to use air temperature to predict product temperature for highest shelf-life prediction accuracy in the absence of individual sensors for each monitored product have been developed. Our results show a significant reduction of up to 98% in the root-mean-square-error difference between the product temperature and air temperature when advanced estimation methods are used.

The Problem

Supply chains have a lot of variability. How can you route individual products to ensure the least waste possible?

supply chain logistics variation
blueberry export example (NW Canada to USA)
simplified overview to illustrate typical supply chain real time variation available for FEFO
we have 10 days difference between the shortest supply chain and the longest supply chain

	supply chain process segment (typical)	shortest (day)	longest (day)
	harvest, sort, pack, storage, ship out (could be ± 0.5 days)	1	1
logistics segments	truck to US brand owner warehouse	2	5
logistics segments	brand owner warehouse storage and shipping	0.5	3
logistics segments	trucking to retailer distribution centre	0.5	2
logistics segments	retailer distribution centre storage and transit to retail store	0.5	2
logistics segments	retail store storage, display and sale	0.5	2
	total supply chain real time	5	15
	quality and safe consumption time (at 10°C storage)	2–7+	2

FEFO versus FIFO pallet level advantages at key decision points would be:

— US warehouse to ship to
— retail distribution centre to ship to
— retail store to ship to
— retail store display location
— inventory rotation at brand owner warehouse
— distribution centre inventory rotation
— retail store inventory rotation
— promotional pricing, mark downs, etc.

Figure 1. Many supply chains have destinations with variable distance and time. FIFO pallet-level inventory and routing is generally based on pallet age from assumed harvest date and visible quality inspections. FEFO pallet-level inventory and routing can be based on multiple factors, but the minimum consideration would be time and temperature history to determine accumulated shelf-life loss between individual pallets, which is typically invisible during physical inspections until it is too late to significantly avoid waste via remaining supply chain adjustments. Pallets with less shelf-life loss can be held in inventory longer and sent on longer routes, when the shelf-life loss variations are known. Pallets with more shelf-life loss should be rotated faster and sent on shorter remaining supply chains. Sending pallets out on an FIFO and visible quality inspection basis can and does create waste, which can be avoided with time and temperature history and FEFO management. (Online version in colour.)

The Problem

Remaining shelf life for berries is based on the product's temperature & humidity history and how it will be stored in the future. Visual inspection of the product can not reliably tell you its remaining shelf life.

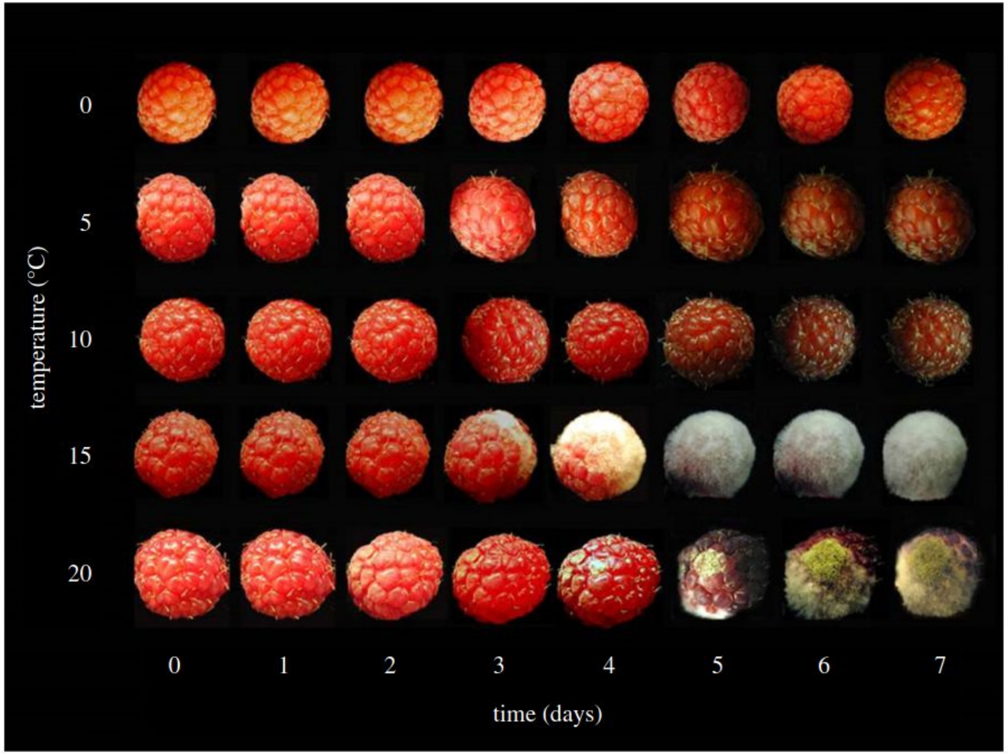


Figure 8. Impact of temperature on the appearance of 'Killarney' red raspberries during a storage period of 7 days [4,6]. (Online version in colour.)

The Problem

Products in the same shipping container can experience very different temperatures.

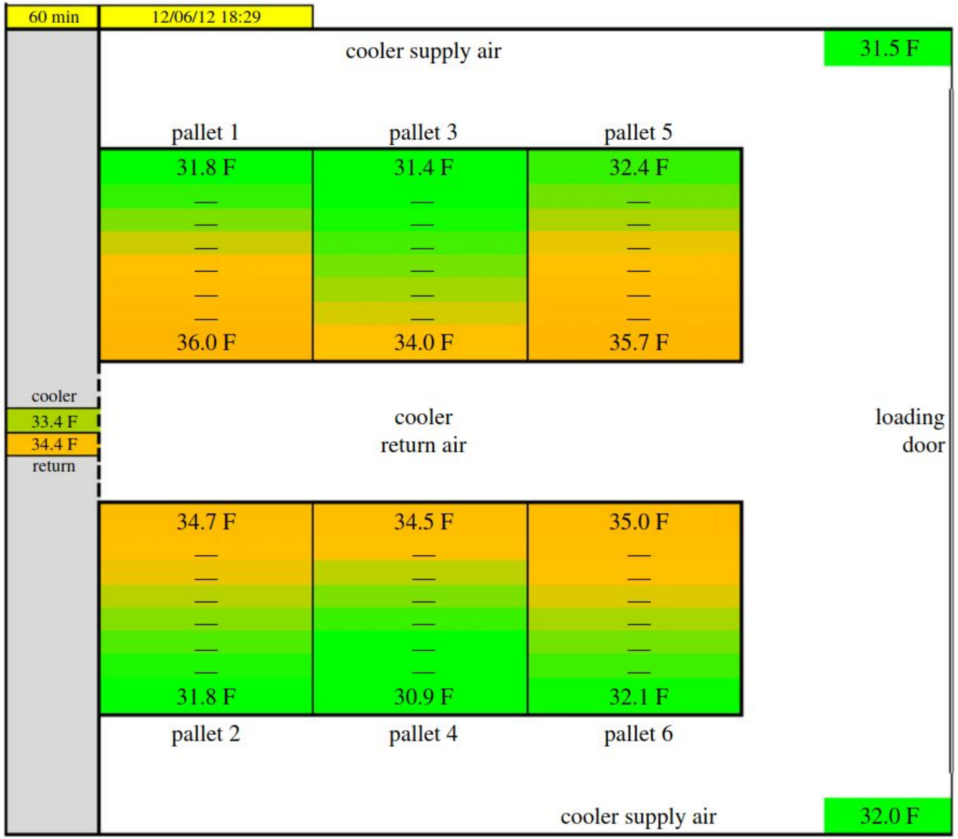


Figure 4. RFID temperature data loggers monitoring supply and return air for each pallet, as well as general pre-cooler supply and return, show individual pallet cooling variations in real time (with permission of ProWare Services LLC and Franwell Inc.) (Online version in colour.)

The Problem

Therefore, products shipped together may have very variable shelf lives

The Problem

It is too difficult/expensive to put temperature sensors everywhere; can only sample the shipping container coarsely.

In order to ensure the longest shelf life, the perishable food products must be kept under controlled temperatures throughout transportation and storage in a well-managed cold chain. Monitoring devices are used to ensure temperature integrity; however, resource limitations and cost factors severely limit their use to one-per-pallet or even one-per-container scenarios. For example, in a traditional shipping scenario with no additional environmental monitoring in place, there are one to three sensors placed inside, expected to represent the wide temperature spectrum in the shipping container. In fact, even when there is additional temperature information available via more extensive use of sensors inside the container, the monitoring resolution rarely goes beyond pallet level. Nevertheless, owing to characteristics of food and insulation of the packaging, the temperature is not always homogeneously distributed inside the pallet, and using a single sensor for the entire pallet does not provide a realistic representation.

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

Data from a precisely-sensed shipping pallet under 3 external climate conditions representing different seasons.

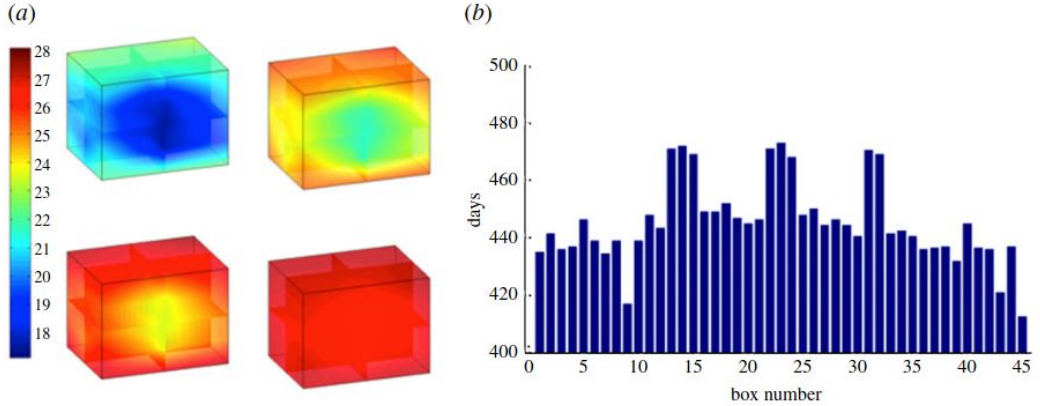


Figure 9. (*a*) Temperature distribution inside a pallet as the container temperature increases (from top left to bottom right); (*b*) shelf life of each box under after a 24 h summer temperature profile. (Online version in colour.)

The FSR pallet used in this study consisted of 45 cartons, each of which is instrumented to measure the product temperature throughout the full duration of a 24 h summer temperature profile. As the temperature inside the container which houses the FSR pallet was varied, differences on the temperature distribution were documented. Cartons closer to the core of the pallet exhibited different temperature dynamic behaviour compared with the exterior cartons (figure 9*a*). As expected, the rate of temperature increase at the centre of the pallet was lower than the outside of the pallet owing to isolation of the cartons and heat transfer dynamics of the food itself. While the average temperature throughout transportation might be similar for all cartons, because the shelf-life losses increase exponentially at higher temperatures, one can observe a significant difference between the remaining predicted shelf lives of products (figure 9*b*). At the

FSR = first strike rations

Models

“Capicator model” - Physical model based on temperature dynamics

“Kriging method” - general purpose spatial interpolation method

Artificial neural network - trained to capture any nonlinear dynamics of temperature flow through products

Models

Artificial neural network

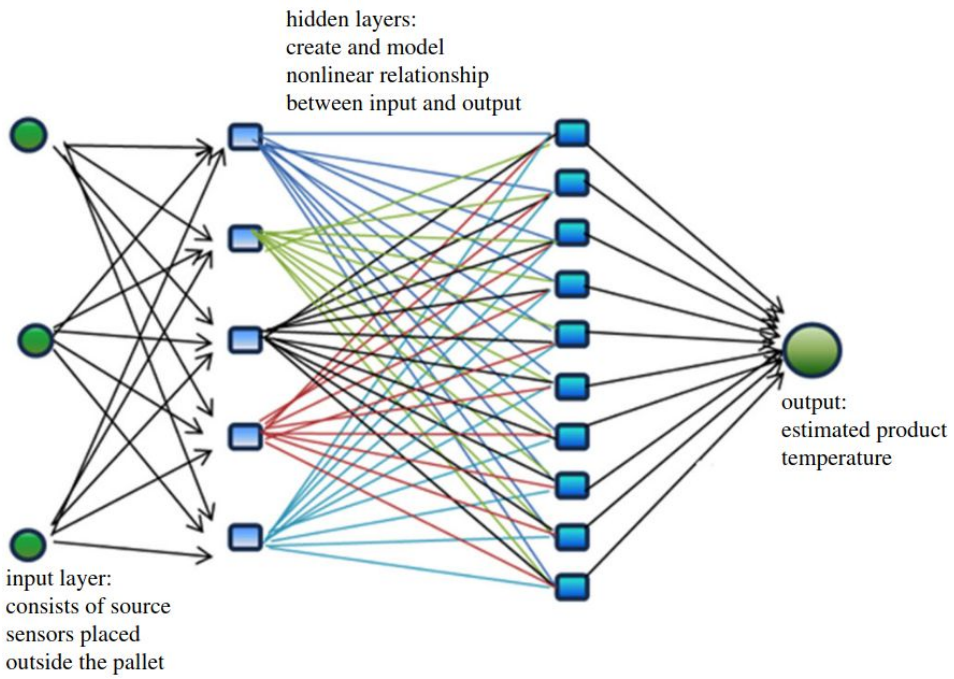


Figure 10. The structure of an artificial neural network to estimate temperature dynamics. (Online version in colour.)

Input to the network consists of time–temperature data provided by the sensor(s) placed outside the pallet, whereas output is the estimated time–temperature data for products placed inside the pallet. ANNs need to be trained with part of the temperature data to learn how to estimate the nonlinear relationship between the input and target output.

Evaluation

Just Root Mean Square Error

“In order to compare the
different estimation algorithms,
we looked at the average
root-mean-
squared error (RMSE) between
actual and estimated
temperatures for each box inside
the pallet”

Results

Results

Table 1. Root-mean-squared errors for estimated and actual product temperatures compared with ambient temperature difference.

experiment	analysis method	average product temperature RMSE (°C)	average air temperature RMSE (°C)
wide range summer profile	capacitor	1.08	11.60
	Kriging	1.15	
	neural network	0.29	
summer profile	capacitor	1.91	3.56
	Kriging	3.30	
	neural network	0.17	
winter profile	capacitor	0.45	3.38
	Kriging	0.89	
	neural network	0.16	

Error if you just assumed product temperature was equal to air temperature

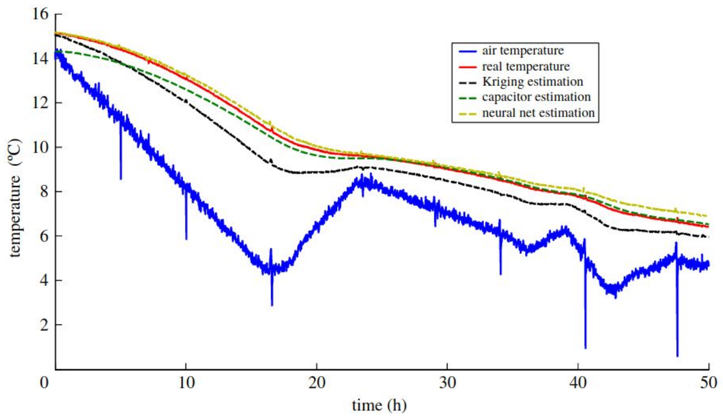


Figure 11. Winter profile temperature estimations. (Online version in colour.)

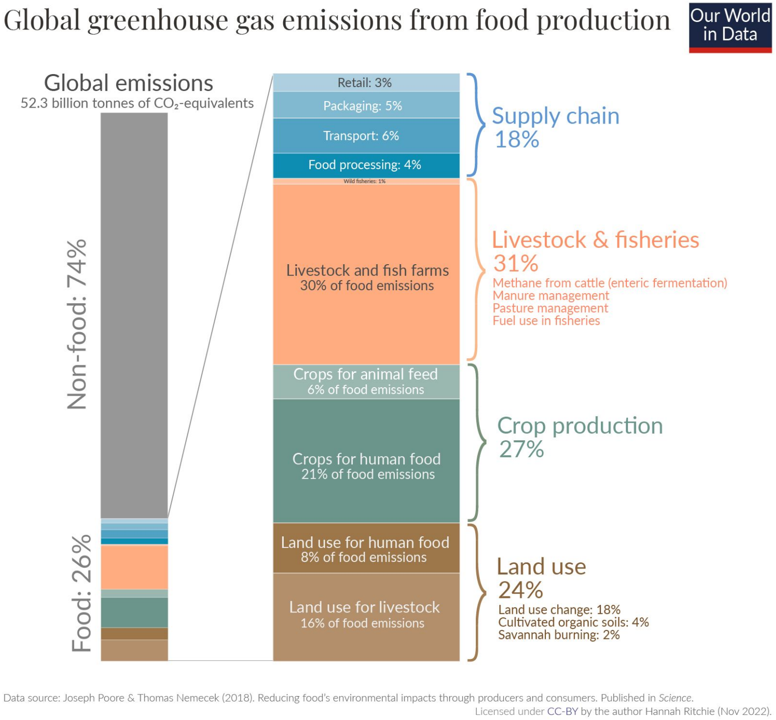
Further resources

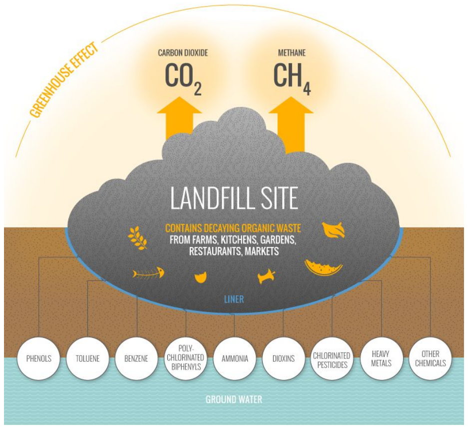
Reports on start-ups fighting food waste:

https://www.washingtonpost.com/climate-solutions/interactive/2021/food-waste-climate-change-strella-biotechnology/

https://www.weforum.org/agenda/2021/06/wasteless-ai-retail-food-waste/

Summary





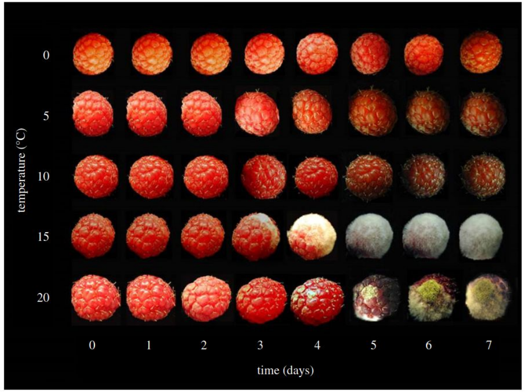


Figure 8. Impact of temperature on the appearance of 'Killarney' red raspberries during a storage period of 7 days [4,6]. (Online version in colour.)