



Carnegie Mellon University
Language Technologies Institute

Carbon and the Future

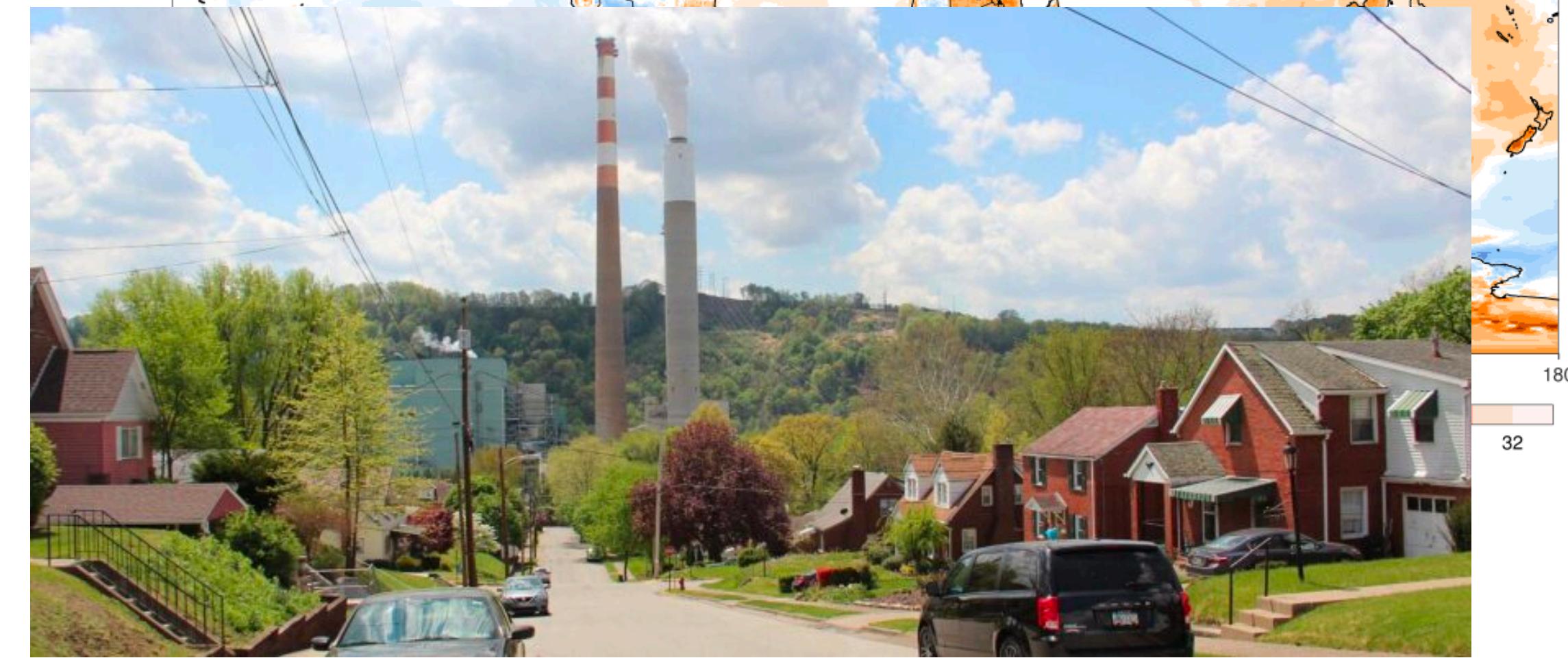
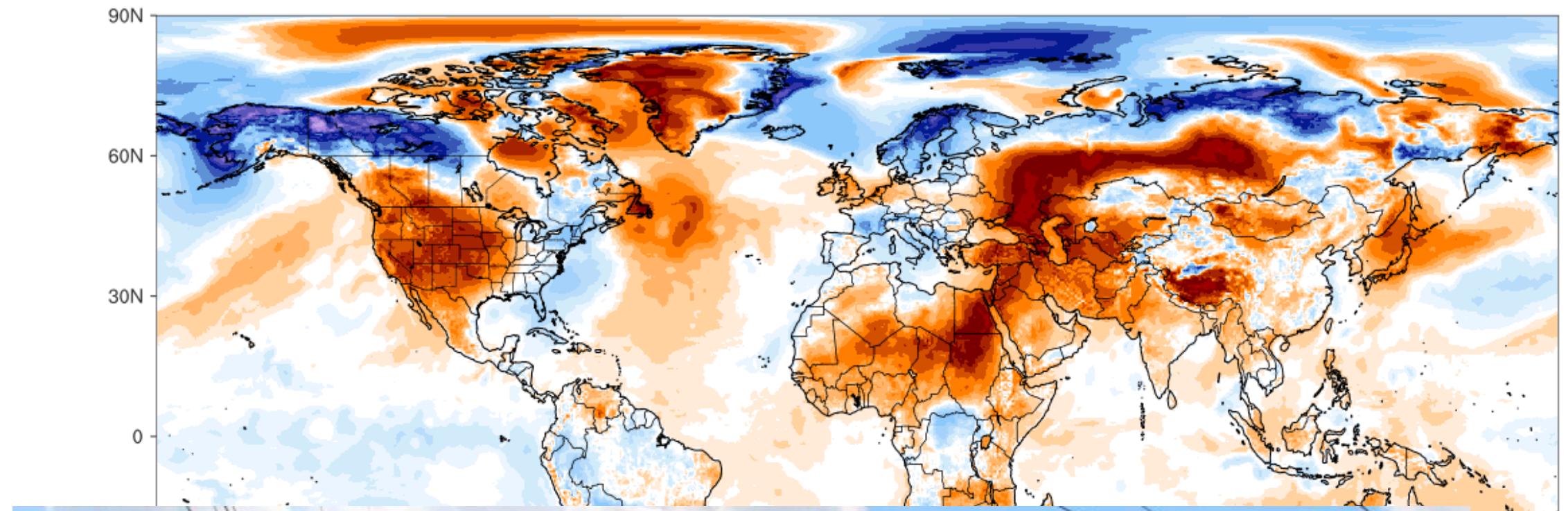
Emma Strubell & Yonatan Bisk

Climate change is real

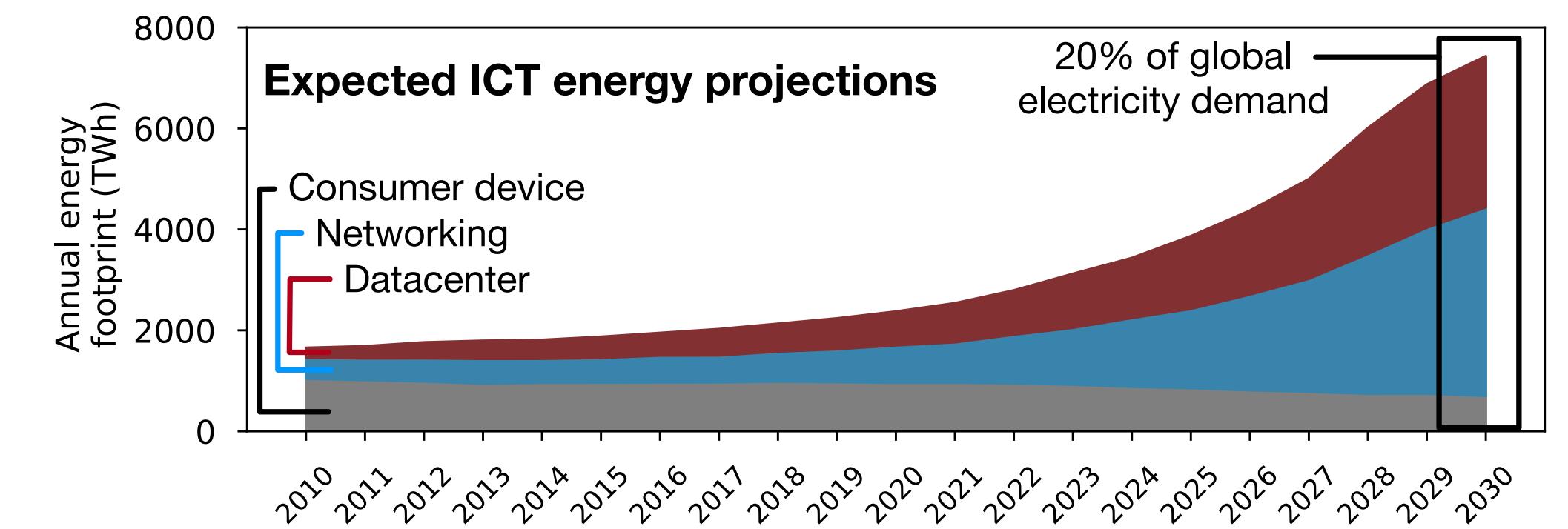
- Humans have already caused 1°C of global warming, likely to reach 1.5°C between 2030–2052 at current rate.
- 1.5–2°C seems to be an inflection point for catastrophic changes in weather, sea levels.
- Limiting global warming to 1.5°C will require rapid and far-reaching transitions in energy, land, urban and infrastructure (including transport and buildings), and industrial systems.

IPCC Special Report: Global Warming of 1.5°C

- Computers use energy, but more importantly, digitization is (re-)shaping the economy. **AI has great potential for positive or negative impact on the climate.**



<https://www.wesa.fm/environment-energy/2021-06-10/pittsburgh-area-coal-fired-power-plant-to-close>



Gupta et al. Chasing Carbon: The Elusive Environmental Footprint of Computing. 2020.



The big picture

The Greenhouse Gas Protocol for quantifying organization-level emissions.

Scope 1

Direct emissions

- Raw material combustion, refrigerants in offices and facilities.
- Burning PFCs, chemicals and gasses in manufacturing.
- Cow farts.

Calculated relative to a specific GHG-emitting entity.

Scope 2

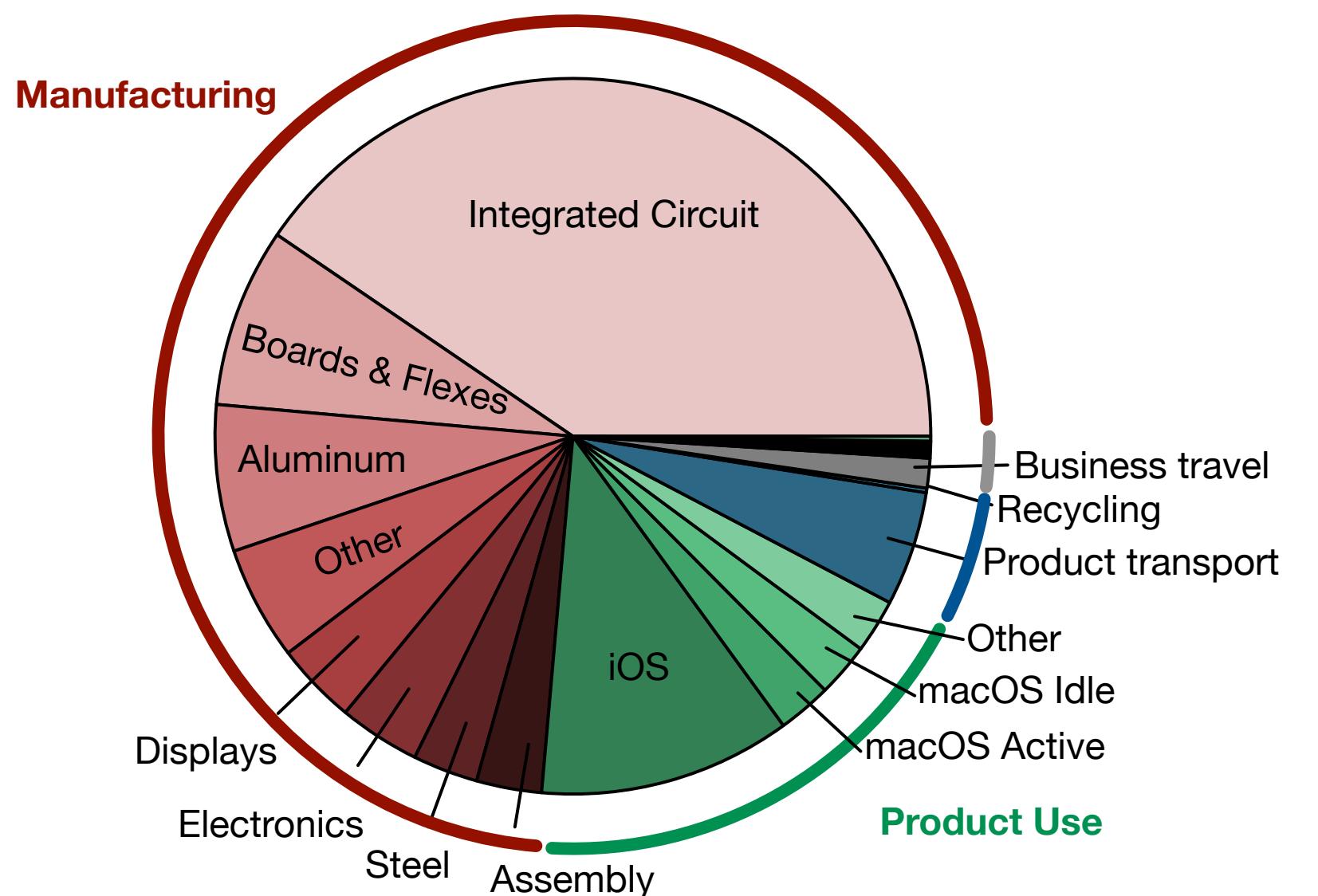
Indirect emissions

- Purchased energy for fabrication, heating and cooling offices, datacenters.
- Training, developing, running ML models.

Scope 3

Up- and down-stream supply chain

- Everything else.
- Facilities construction.



Apple's carbon emission breakdown: 98% due to hardware lifecycle



Supply Chain

How much of your carbon footprint happens before you enter the picture?

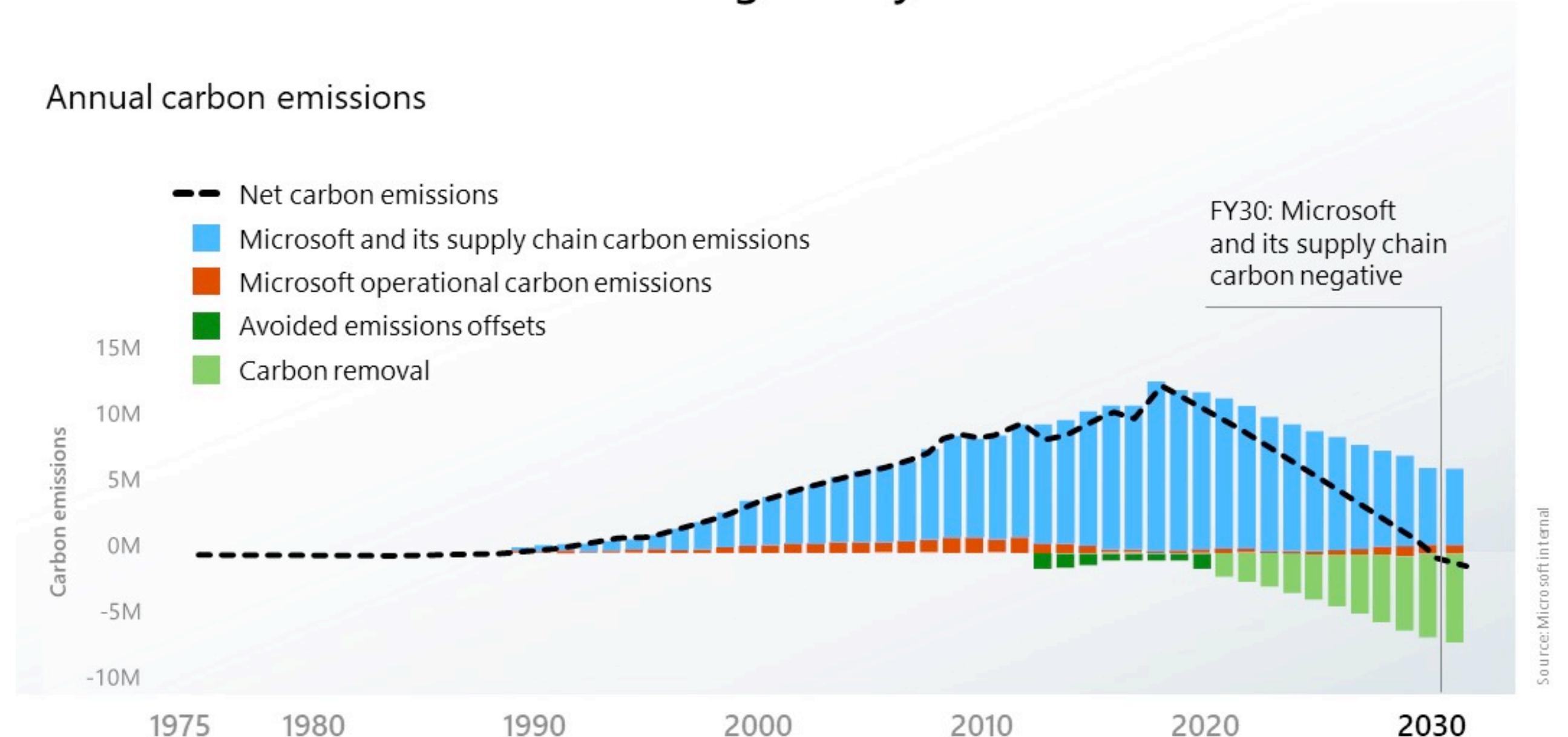
13-inch MacBook Pro life cycle carbon emissions

76%	Production
6%	Transport
17%	Use
<1%	End-of-life processing

iPhone 13 life cycle carbon emissions

81%	Production
2%	Transport
16%	Use
<1%	End-of-life processing

Microsoft's pathway to carbon negative by 2030



<https://blogs.microsoft.com/blog/2020/01/16/microsoft-will-be-carbon-negative-by-2030/>

Google: Operating Net Zero
<https://sustainability.google/commitments/>

Apple: Operating + Supply Chain Net Zero
<https://www.apple.com/newsroom/2020/07/apple-commits-to-be-100-percent-carbon-neutral-for-its-supply-chain-and-products-by-2030/>

Carbon Capture vs Carbon Offsets

CO₂ Removal

Carbon dioxide removal (CDR), also known as negative CO₂ emissions, is a process in which carbon dioxide gas (CO₂) is **removed from the atmosphere** and sequestered for long periods of time

https://en.wikipedia.org/wiki/Carbon_dioxide_removal

Plant a tree 

Carbon Capture and Storage

Carbon capture and storage (CCS) or carbon capture and sequestration is the process of capturing carbon dioxide (CO₂) **before it enters the atmosphere**, transporting it, and storing it (carbon sequestration) for centuries or millennia.

https://en.wikipedia.org/wiki/Carbon_capture_and_storage

You burn it? Catch it!

Carbon Offsets

A carbon offset is a reduction or removal of emissions of carbon dioxide or other greenhouse gases made in order to **compensate for emissions made elsewhere**

https://en.wikipedia.org/wiki/Carbon_offset

It's complicated...



Carbon Offsets

Guiding Philosophy: Someone needs to pay (also idea behind a carbon tax)

Burn all the coal → Pay for a wind farm that will hopefully someday replace you

Take that vacation → Pay for a materials science research lab on battery tech

Build a house → Donate to forest preservation

Problem: We need right column regardless, so it doesn't really “cancel” out column A

The big picture

The Greenhouse Gas Protocol for quantifying organization-level emissions.

Scope 1

Direct emissions

- Microsoft will be carbon negative by 2030

Jan 16, 2020 | [Brad Smith - President & Vice Chair](#)



[Microsoft will be carbon negative by 2030](#)

Scope 2

Indirect emissions

- Energy for heating, cooling, lighting, and water
- Electricity used in manufacturing processes
- Electricity used in business travel
- Electricity used in purchased goods and services
- Electricity used in waste management
- Electricity used in downstream supply chain

Scope 3

Up- and down-stream supply chain

- Everything else.

ExxonMobil to increase Permian profitability through digital partnership with Microsoft

February 22, 2019 | [Microsoft News Center](#)



- Permian application to generate billions of dollars in value over the next decade and drive capital efficiency
- Potential to expand production by as much as 50,000 oil-equivalent barrels a day by 2025
- Largest-ever oil and gas acreage to use cloud technology

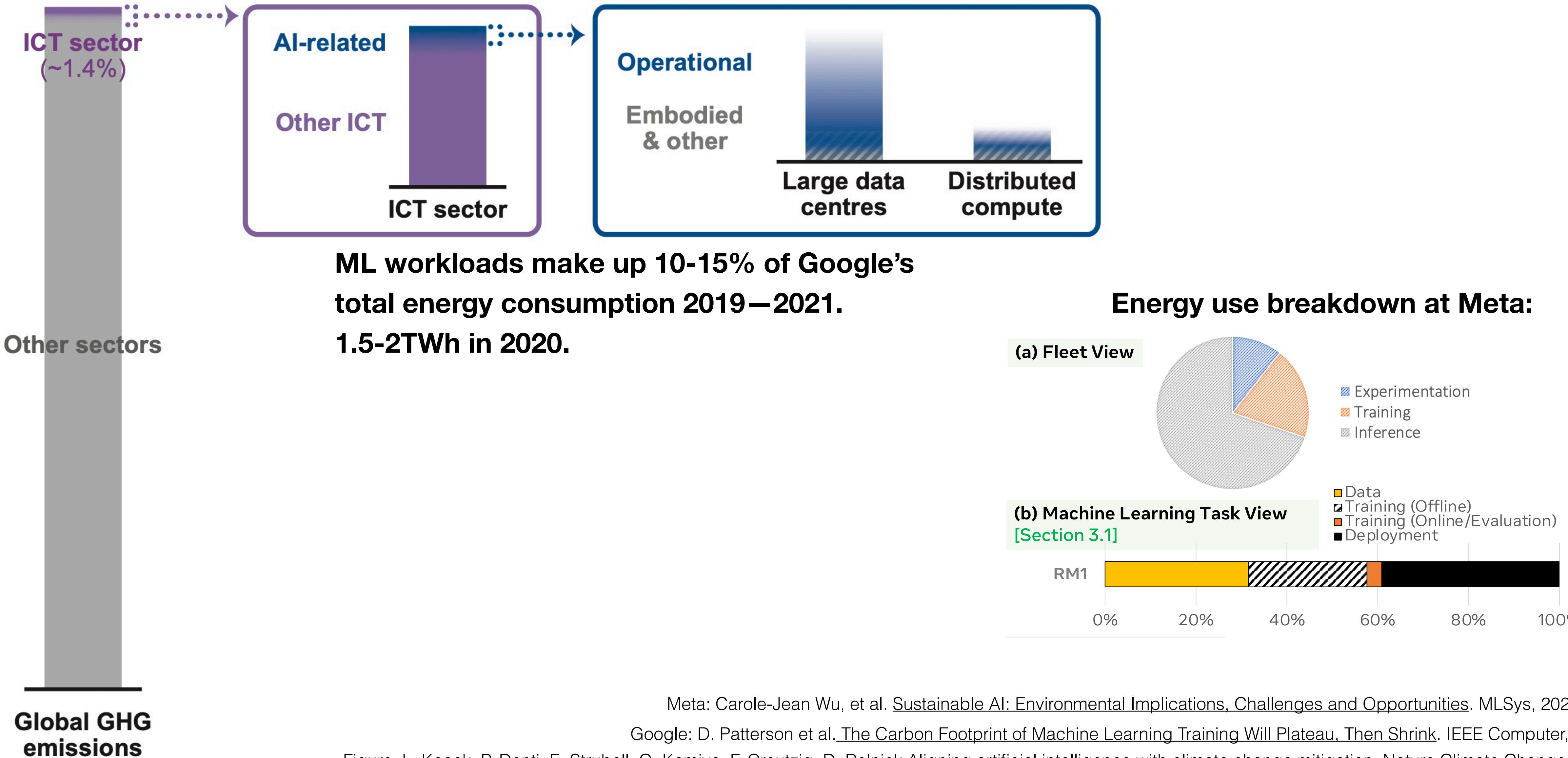
IRVING, Texas — February 22, 2019 — ExxonMobil said today a new partnership with Microsoft Corp. will make its Permian Basin operations the largest-ever oil and gas acreage to use cloud technology and is expected to generate billions in net cash flow over the next decade through improvements in analyses and enhancements to operational efficiencies.

The application of Microsoft technologies by ExxonMobil's XTO Energy subsidiary – including Dynamics 365, Microsoft Azure, Machine Learning and the Internet of Things – is anticipated to improve capital efficiency and support Permian production growth by as much as 50,000 oil-equivalent barrels per day by 2025.

[ExxonMobil to increase Permian profitability through digital partnership with Microsoft](#)



Operational emissions: ML model lifecycle



The big picture: Framework for AI + climate

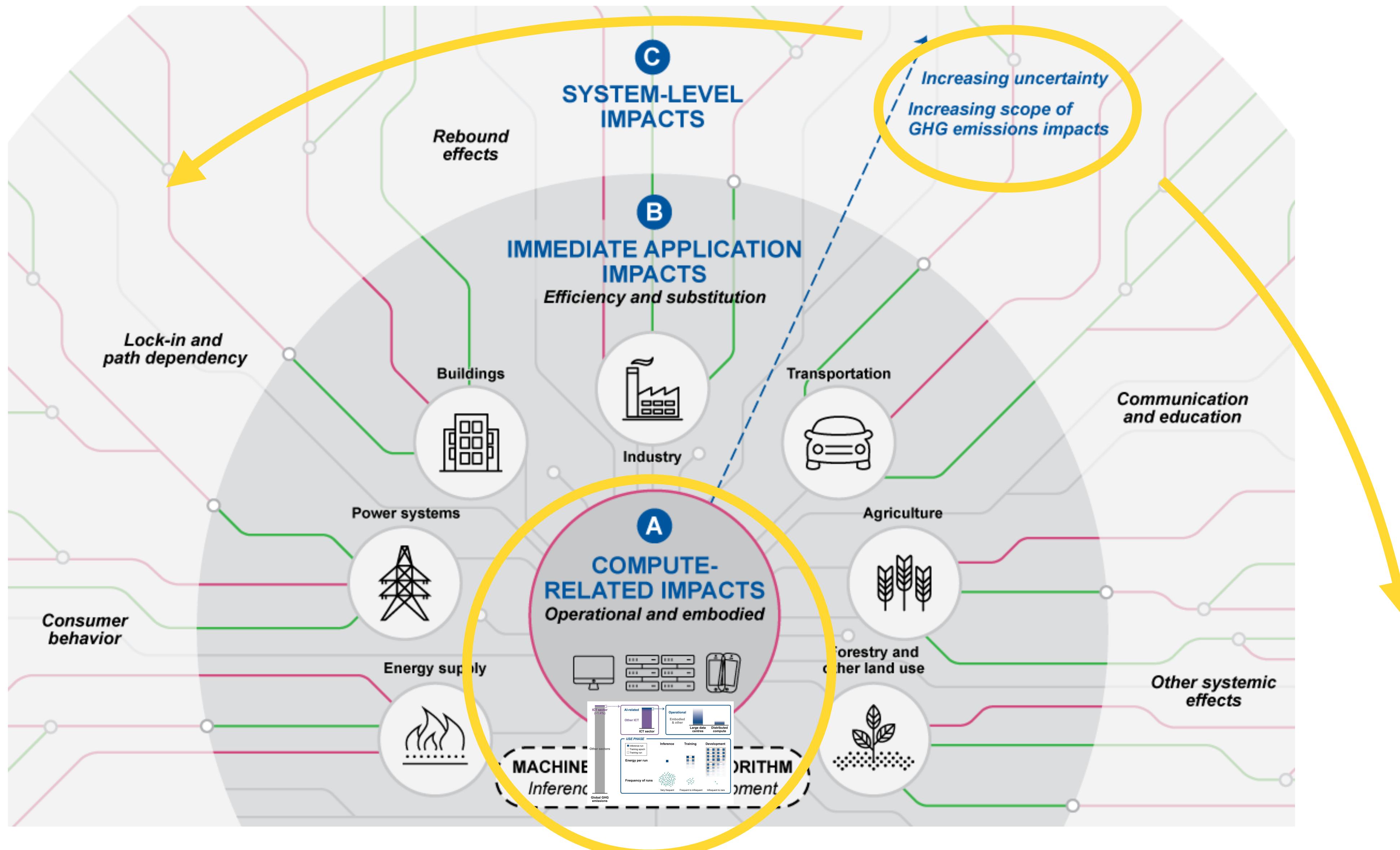


Figure: L. Kaack, P. Donti, E. Strubell, G. Kamiya, F. Creutzig, D. Rolnick [Aligning artificial intelligence with climate change mitigation](#). Nature Climate Change, 2022.

The big picture: Framework for AI + climate

Role of machine learning

Data mining & remote sensing

Accelerated experimentation

Fast approximate simulation

Forecasting

System optimization and control

Predictive maintenance

GHG emissions impact

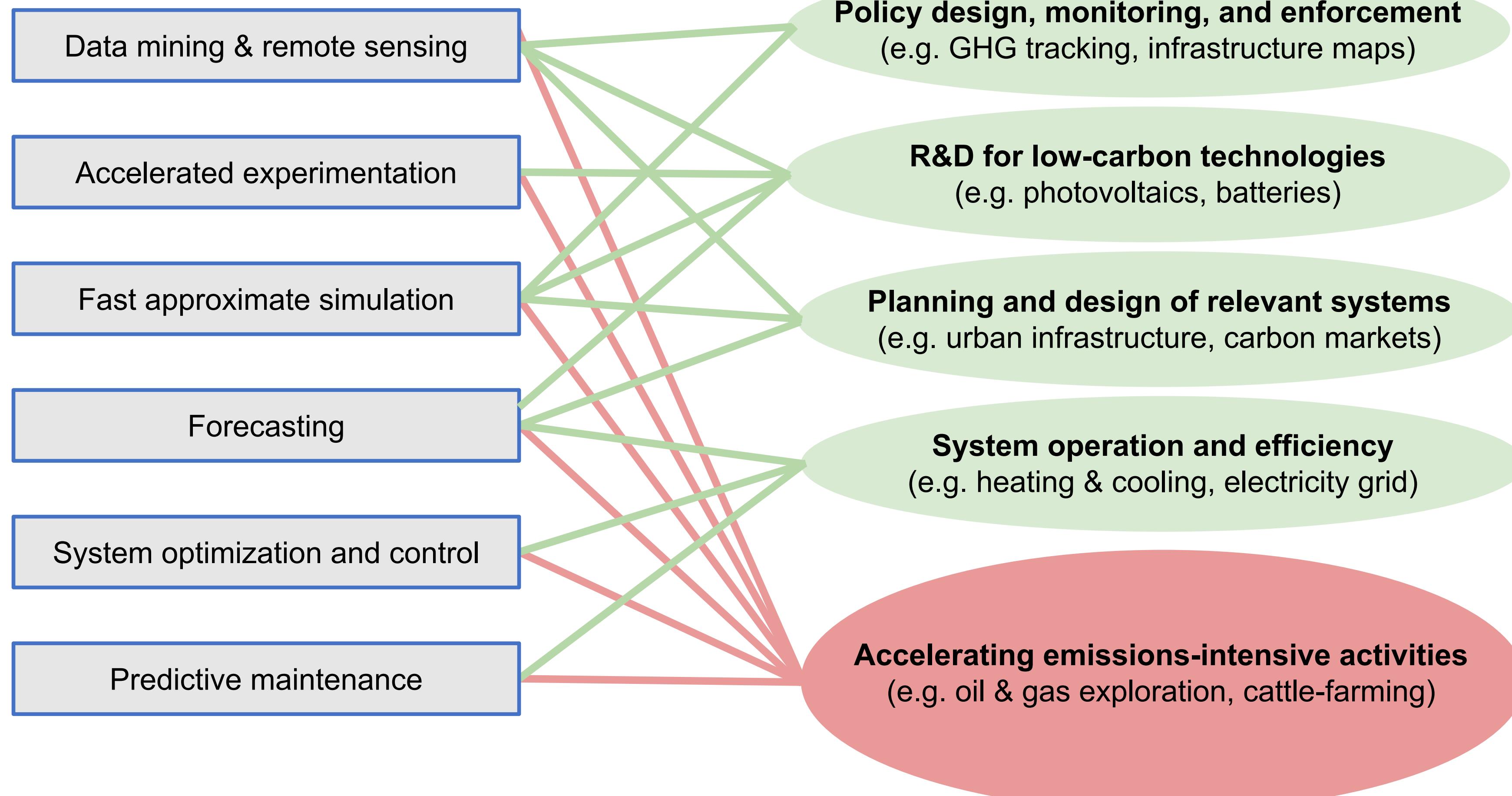
Policy design, monitoring, and enforcement
(e.g. GHG tracking, infrastructure maps)

R&D for low-carbon technologies
(e.g. photovoltaics, batteries)

Planning and design of relevant systems
(e.g. urban infrastructure, carbon markets)

System operation and efficiency
(e.g. heating & cooling, electricity grid)

Accelerating emissions-intensive activities
(e.g. oil & gas exploration, cattle-farming)



Discovering and decarbonizing materials

Materials synthesis

Photovoltaics, batteries and compute hardware.



Materials decarbonization

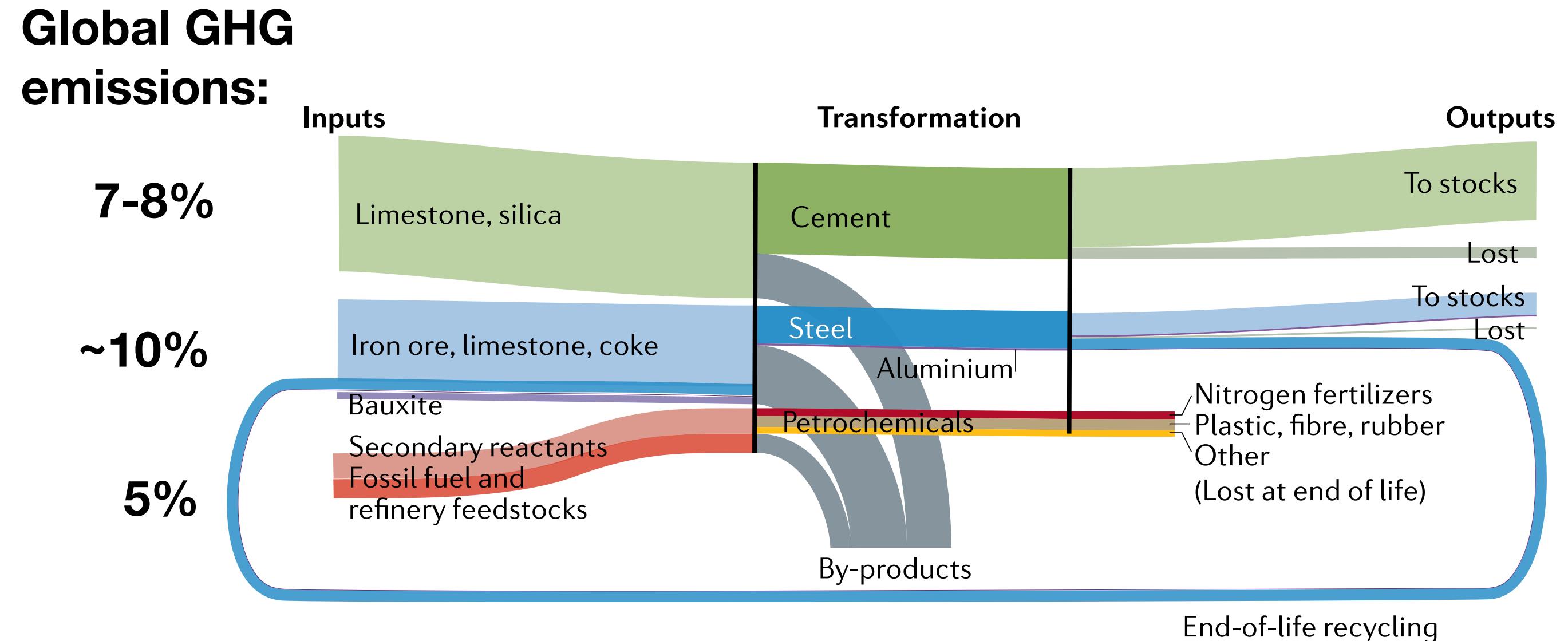
Cement, steel and petrochemicals

Global GHG emissions:

7-8%

~10%

5%



NLP for accelerating scientific discovery

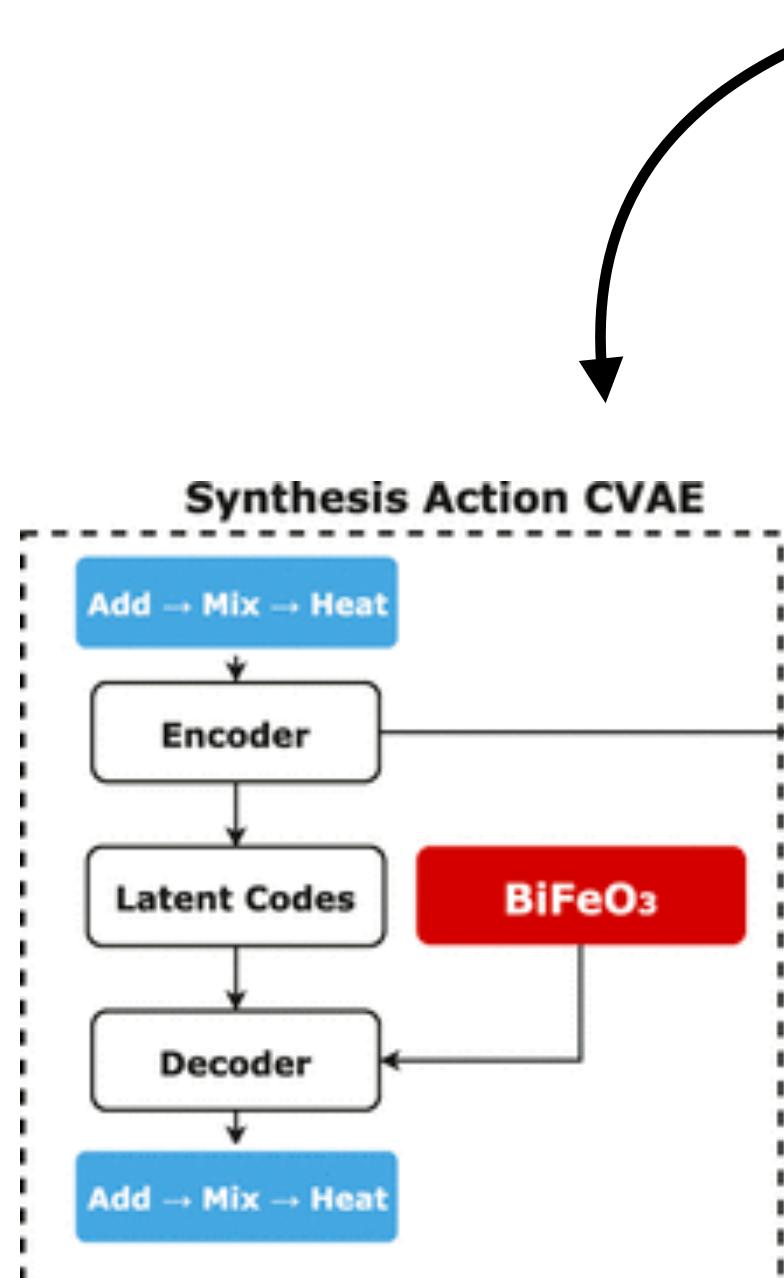
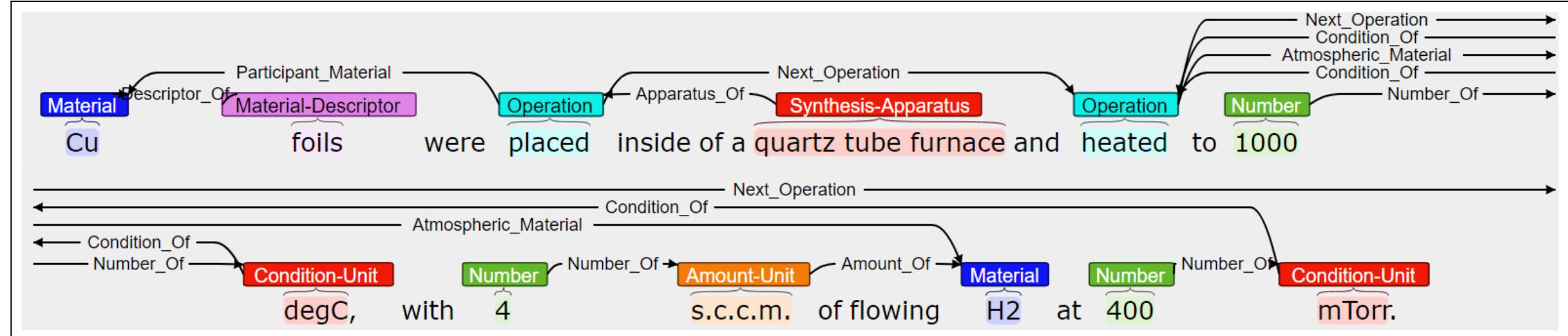
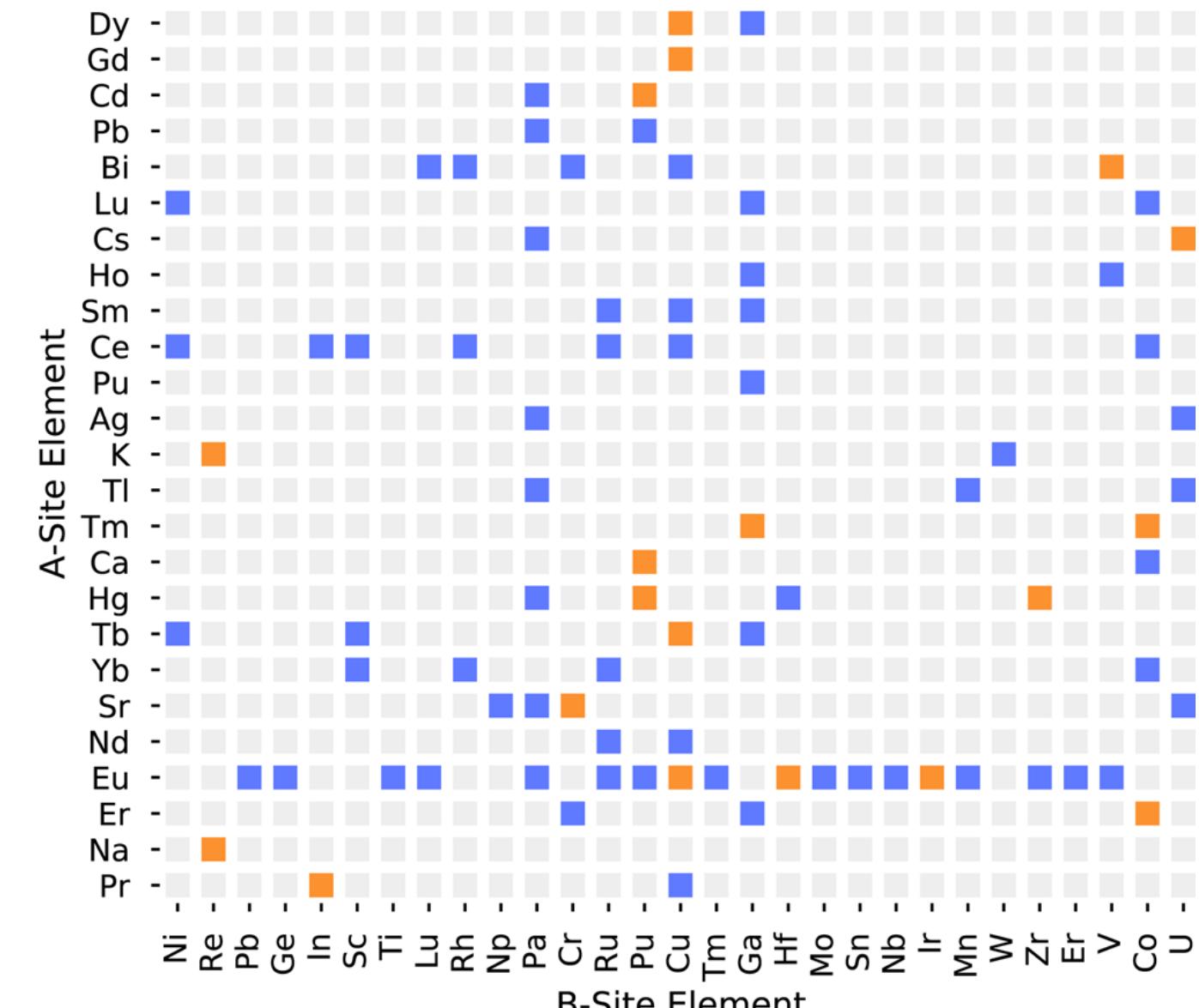


Table 1. Generated Precursors for InWO_3 and PbMoO_3 , Drawn from the CVAE Model^a

target material	precursors
InWO_3	$\text{In}_2\text{S}_3 + \text{WCl}_4$ $\text{In}(\text{NO}_3)_3 + \text{WCl}_4$ $\text{In}_2\text{O}_3 + \text{WO}_2$ $\text{In}_2\text{O}_3 + \text{WN}$ ^b $\text{InCl}_3 + \text{Na}_2\text{WO}_4$
PbMoO_3	$\text{PbCl}_2 + \text{MoCl}_2$ $\text{PbSO}_4 + \text{MoCl}_2$ ^c $\text{PbO} + \text{MoO}_2$

^aThe CVAE model was trained on synthesis routes published during or before 2005. ^bPrecursors match Kamalakkannan et al. (2016).³¹

^cPrecursors match Takatsu et al. (2017).³²



S. Mysore, Z. Jensen, E. Kim, K. Huang, H. Chang, E. Strubell, J. Flanigan, A. McCallum, E. Olivetti.

The Materials Science Procedural Text Corpus: Annotating Materials Synthesis Procedures with Shallow Semantic Structures. LAW, 2019.

E. Kim, Z. Jensen, A. van Grootel, K. Huang, M. Staib, S. Mysore, H. Chang, E. Strubell, A. McCallum, S. Jegelka, E. Olivetti.

Inorganic Materials Synthesis Planning with Literature-Trained Neural Networks. J. Chem. Inf. Modeling, 2020.

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- **Training, developing, running ML models.**

Scope 3

Up- and down-stream supply chain

- Everything else.
- Facilities construction.
- Business travel, commuting, logistics.
- Raw materials.
- Downstream use.

Calculated relative to a specific GHG-emitting entity.



Calculating Carbon

- How we estimated carbon emissions due to model training (Strubell et al. 2019).
- Assumes you have access to power draw (device: RPi4, Jetson 4GB)

$$p_t = 1.58 \frac{t(p_c + p_r + gp_g)}{1000} \text{ kWh}$$

power consumption during training

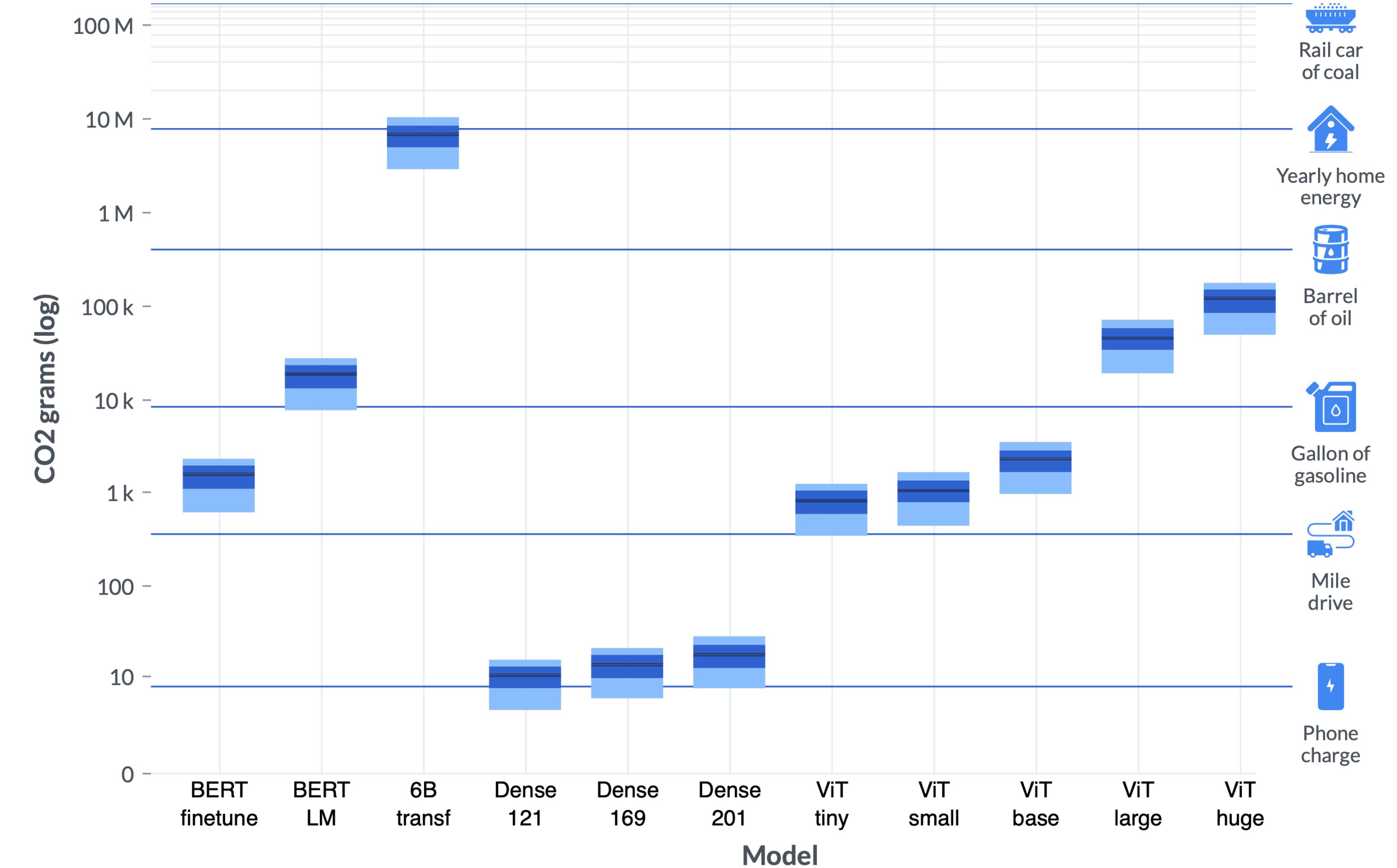
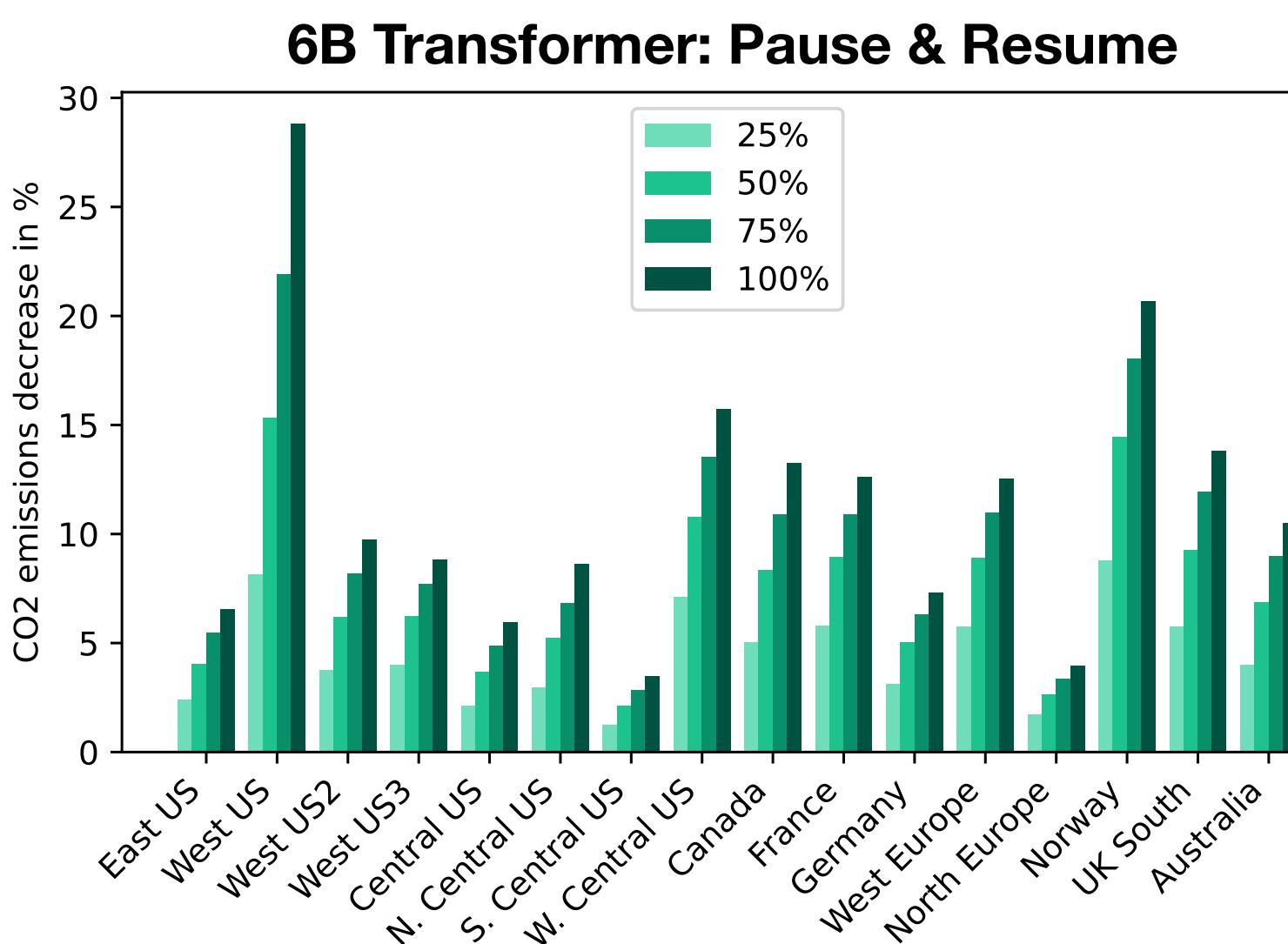
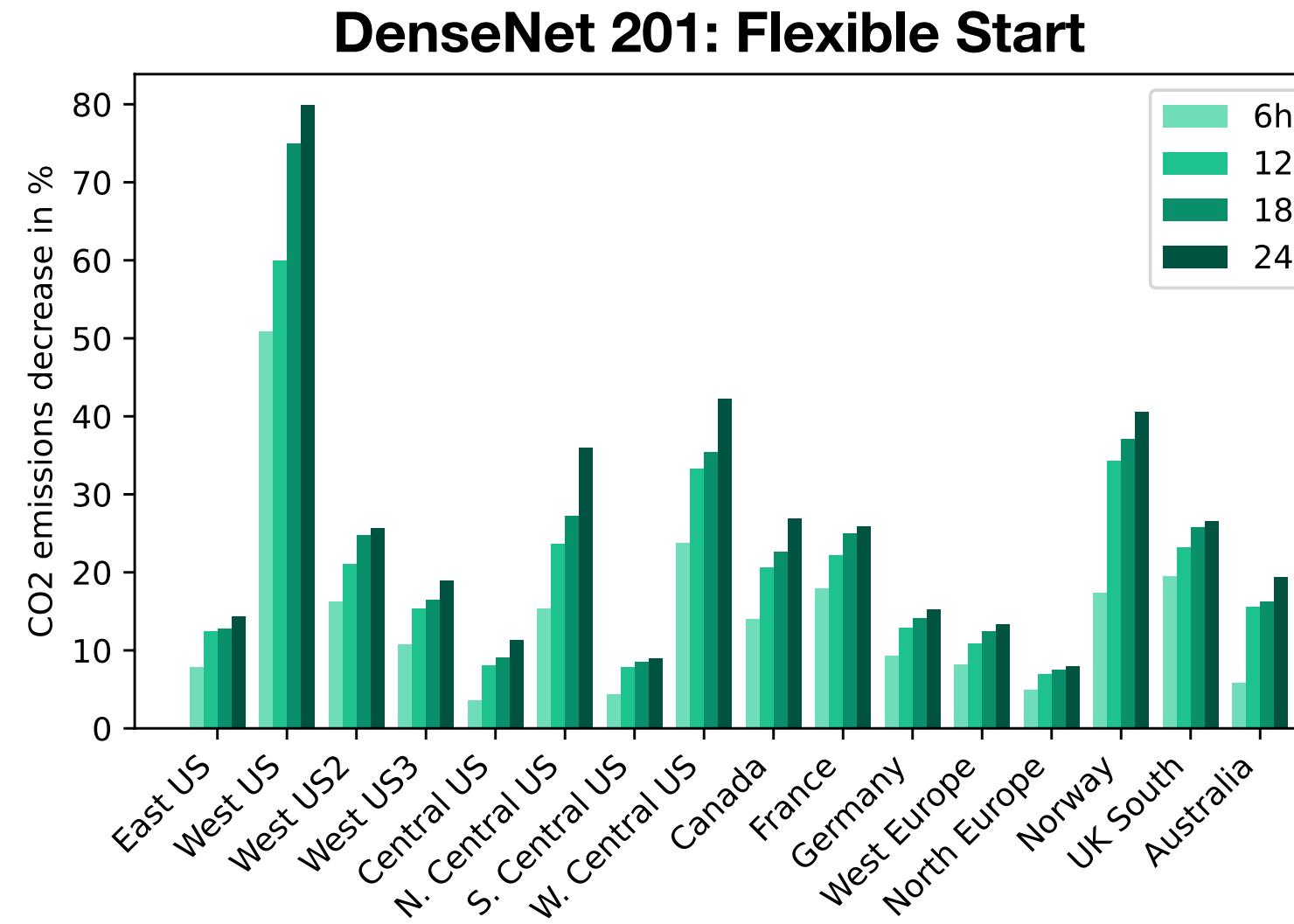
The diagram illustrates the calculation of power consumption (p_t) in kWh. It starts with the formula $p_t = 1.58 \frac{t(p_c + p_r + gp_g)}{1000}$. Arrows point from each term to its definition: t is labeled 'training time' in green; p_c , p_r , and gp_g are labeled 'power draw' in red; and the coefficient 1.58 is labeled 'PUE' in blue.


$$\text{CO}_2\text{e} = 0.954 p_t \text{ pounds}$$

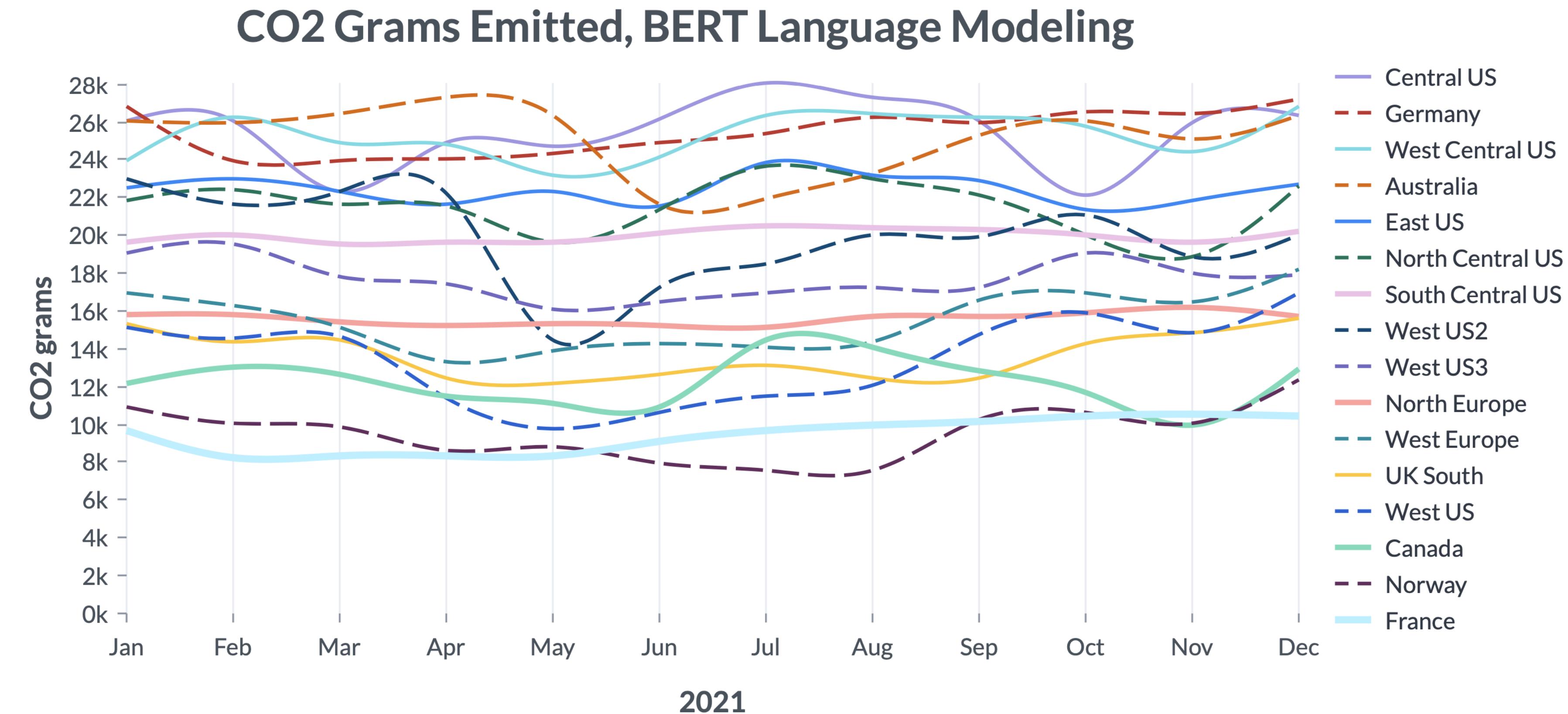
carbon emissions

The diagram illustrates the calculation of carbon emissions (CO_2e) in pounds. It starts with the formula $\text{CO}_2\text{e} = 0.954 p_t$. Arrows point from each term to its definition: p_t is labeled 'power consumption during training' in black; 0.954 is labeled 'U.S. average emissions (EPA)' in blue; and the label 'pounds' is placed next to the result.

Case study: Training large models at Microsoft



Case study: Training large models at Microsoft



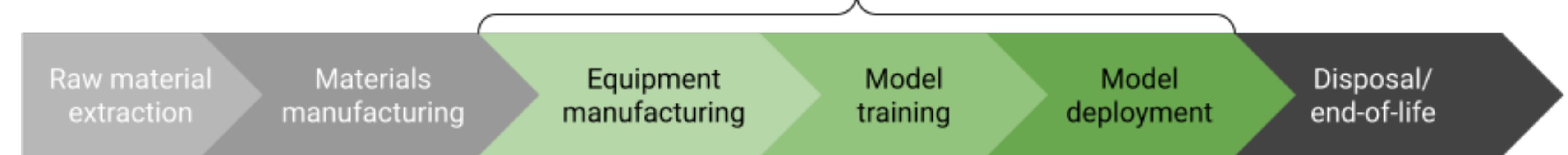
Case study: Training BLOOM (176B params)

Total training time	118 days, 5 hours, 41 min
Total number of GPU hours	1,082,990 hours
Total energy used	433,196 kWh
GPU models used	Nvidia A100 80GB
Carbon intensity of the energy grid	57 gCO ₂ eq/kWh



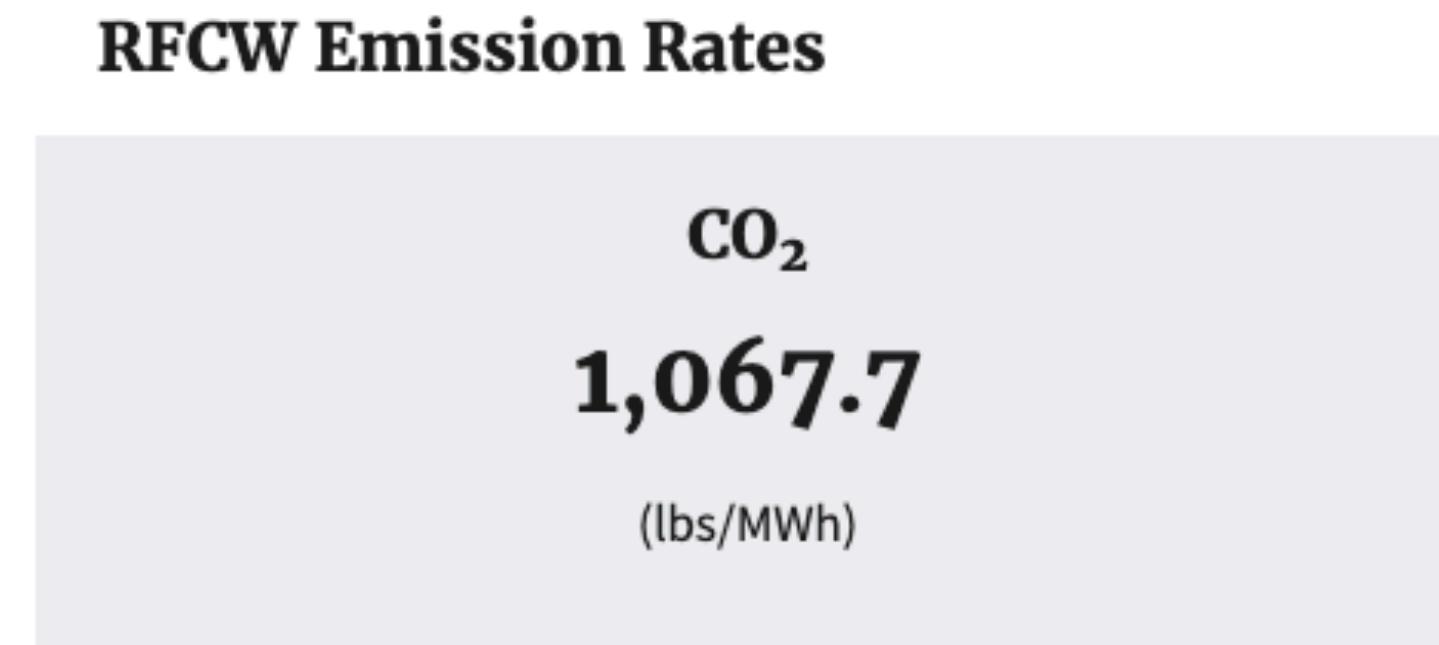
Process	CO ₂ emissions (CO ₂ eq)	Percentage of total emissions
Embodied emissions	11.2 tonnes	22.2 %
Dynamic consumption	24.69 tonnes	48.9 %
Idle consumption	14.6 tonnes	28.9 %
Total	50.5 tonnes	100.00%

**19 kgs CO₂ emitted per day of deployment
75% of energy due to serving the model**



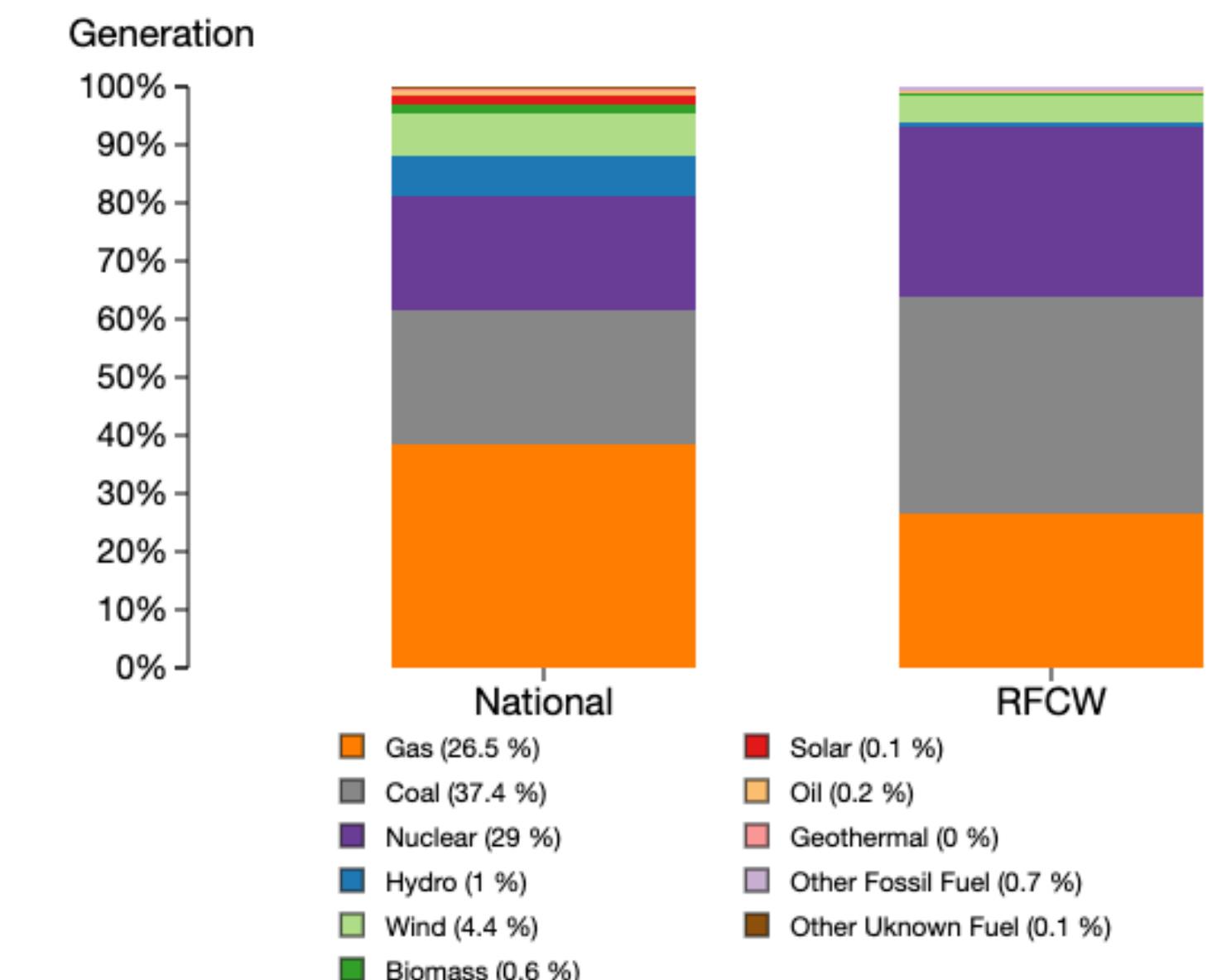
Calculating Carbon

- Most accurate: Direct measurement at the wall using meter
- Jetson 2GB: this is your only option. Others: can compare!
- Still need to convert to emissions.
 - Coarse: <https://www.epa.gov/egrid/power-profiler>
 - Fine-grained: WattTime API



Fuel Mix

This chart compares fuel mix (%) of sources used to generate electricity in the selected [eGRID subregion](#) to the national fuel mix (%).



Calculating Carbon

- In the cloud: Machine Learning Emissions Calculator (Lacoste et al. 2019).
- On device: CodeCarbon

Machine Learning Emissions Calculator

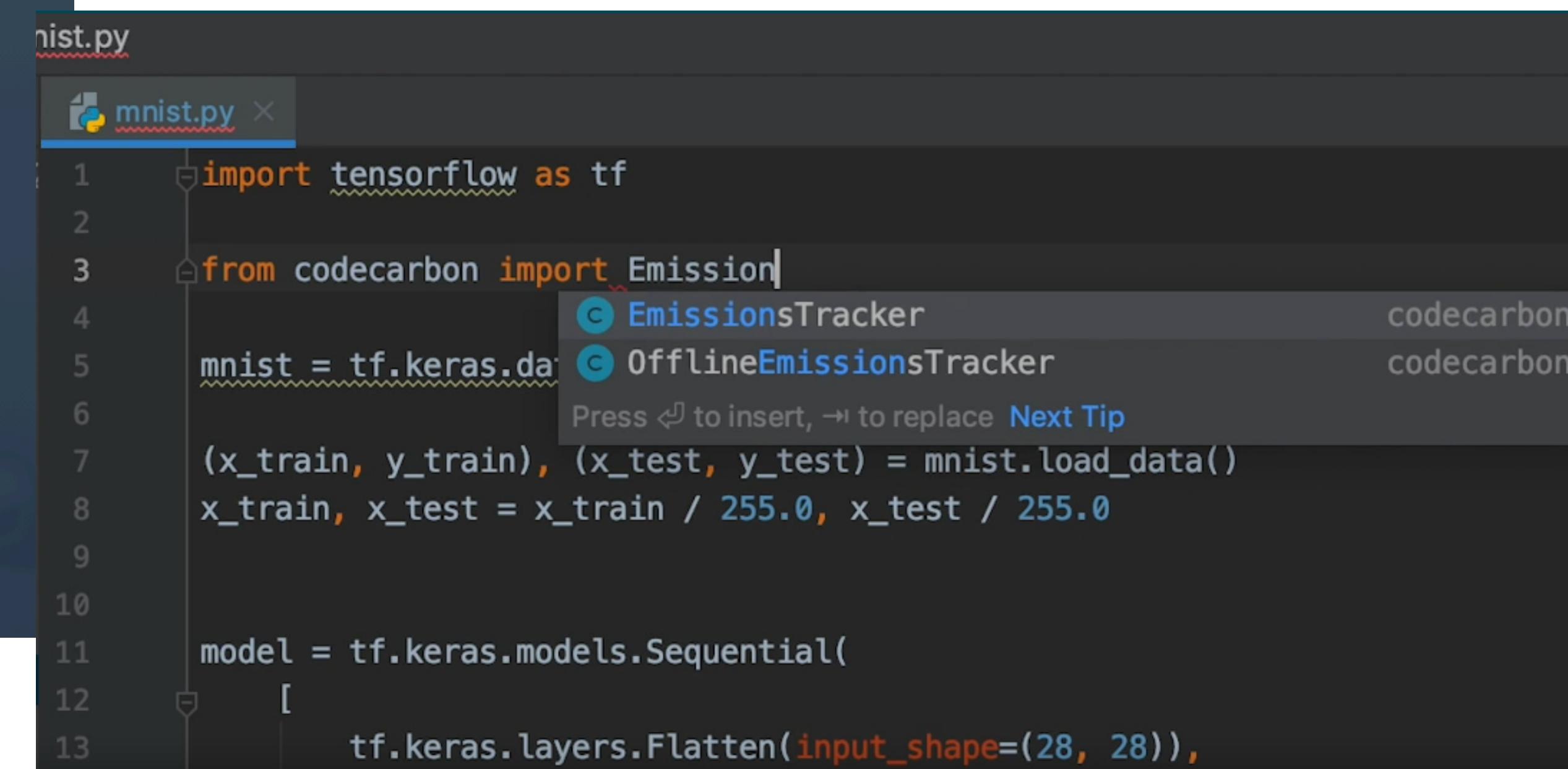
Choose your hardware, runtime and cloud provider to estimate the carbon impact of your research.

This calculator will give you 2 numbers: the **raw** carbon emissions produced and the approximate **offset** carbon emissions. The latter number depends on the grid used by the cloud provider and we are open to update our estimates if anything looks inaccurate or outdated.

Missing a Hardware or a region? Open an issue or a PR on [Github](#)

Hardware type	Hours Used	Provider	Region of Compute
A100 PCIe 40/80G	100	Google Cloud Plat	asia-east1

COMPUTE



```
mnist.py
1 import tensorflow as tf
2
3 from codecarbon import Emission
4   EmissionsTracker
5   OfflineEmissionsTracker
6
7 mnist = tf.keras.datasets.mnist
8 (x_train, y_train), (x_test, y_test) = mnist.load_data()
9 x_train, x_test = x_train / 255.0, x_test / 255.0
10
11 model = tf.keras.models.Sequential(
12 [
13     tf.keras.layers.Flatten(input_shape=(28, 28)),
```

