Tracking greenhouse gas emissions

Estimating and measuring emissions

Climate change in the news

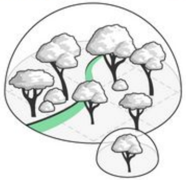
The Guardian

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

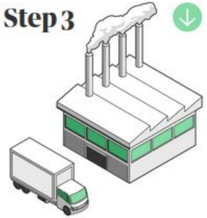
A project is established to mitigate global heating. Many are avoided-emission projects that prevent greenhouse gases from being released from deforestation or fossil fuels, but do not remove carbon from the atmosphere.

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

Assignments

Brightspace discussion question:

“Which do you think plays a bigger role in driving greenhouse gas reductions: government or companies? Why?”

Due this Friday by 5pm.

Climate change in the news

Climate change in the news

ENERGY

At $1.1 trillion, renewable energy investment matches fossil fuels in 2022 for 1st time: BloombergNEF

The hydrogen sector received least boost at $1.1 billion but the sector grew the fastest, tripling investment every year

NEXT NEWS ›

By Seema Prasad
Published: Friday 27 January 2023

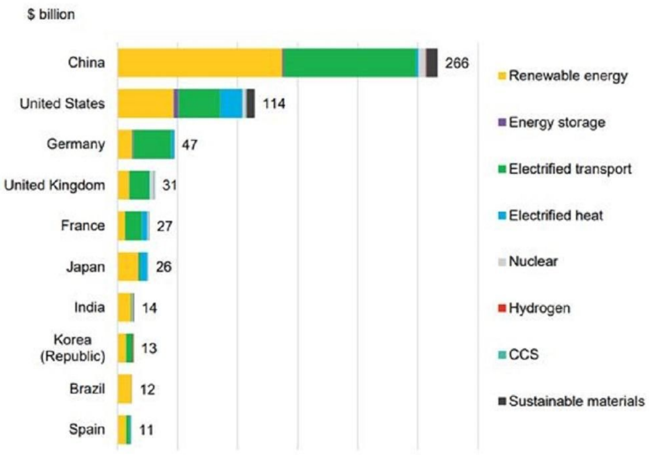
The amount of investment in cleaner energy technology in 2022 was $1.1 trillion, a study by the organisation noted. This came despite an uptick in spending on fossil fuels as many regions focused their attention on energy security, it added.

Investment towards energy transition grew by $261 billion from the previous year — a 31 per cent increase from 2021. But the investment in fossil fuels was also simultaneously up $214 billion over 2021 levels.

Other than nuclear power, which did not see much growth in the last year, all the other sectors surpassed record levels of investment. Electrified heat received $64 billion, energy storage investment reached $15.7 billion and carbon capture and storage hit $6.4 billion, the findings in the report showed.

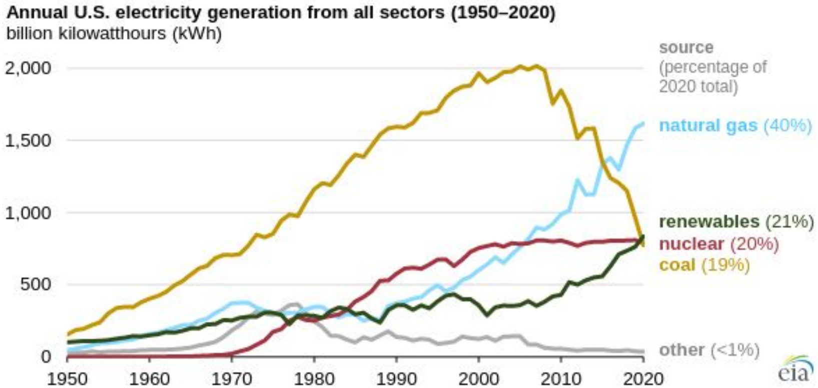
The hydrogen sector received the least boost at $1.1 billion but the sector grew the fastest, tripling investment every year.

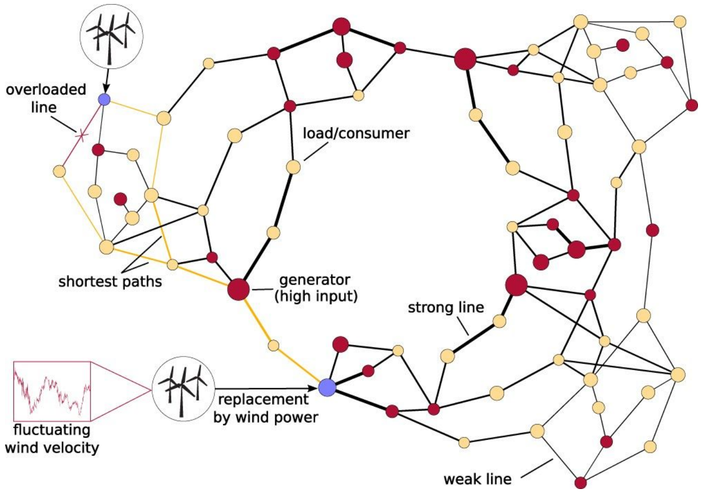
Global investment in energy transition by country, 2021

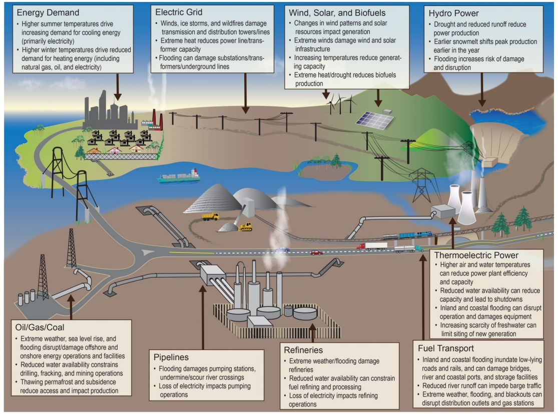


Source: BloombergNEF

Summary



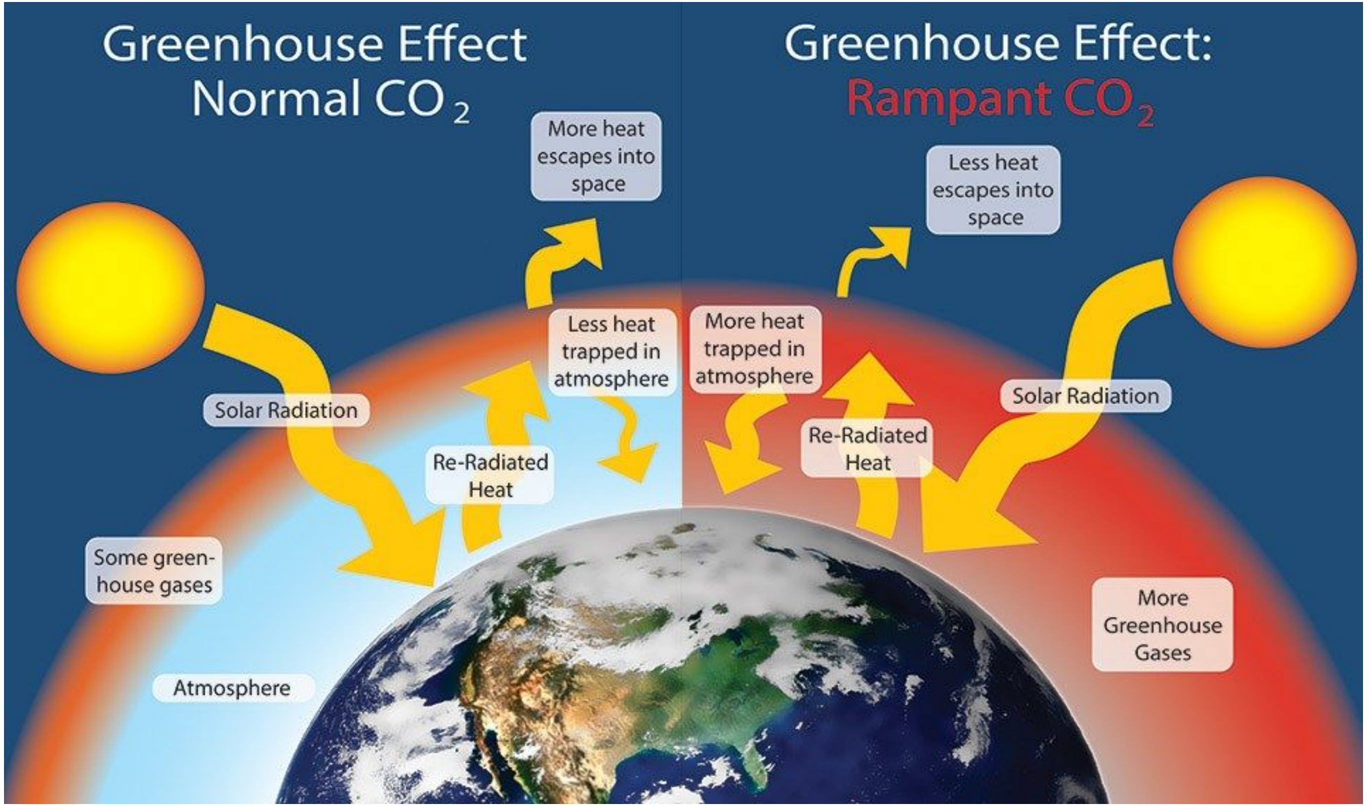




Machine Learning for AC Optimal Power Flow

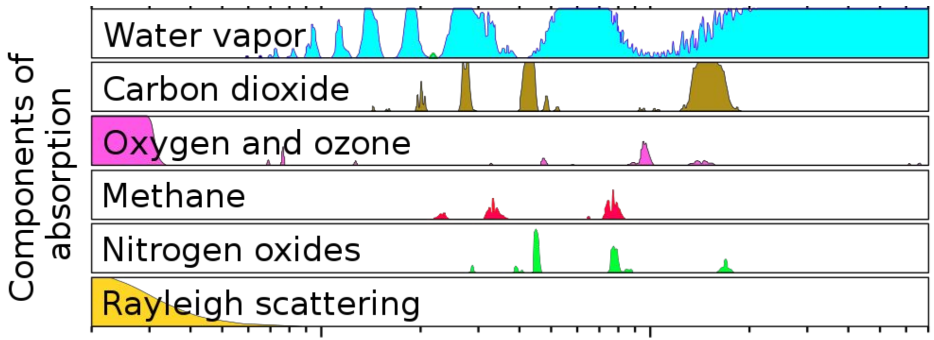
Neel Guha [1] Zhecheng Wang [2] Matt Wytock [3] Arun Majumdar [2]

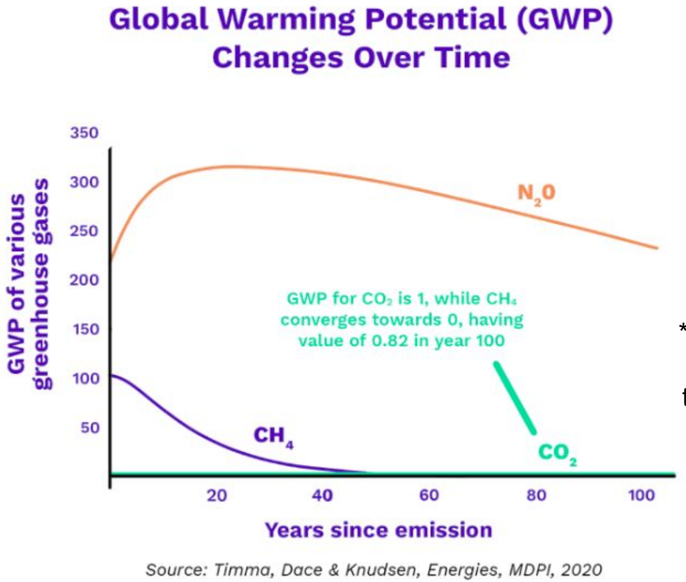
Greenhouse gases



Measuring different GHGs

Chemical structure determines the absorption properties of gases

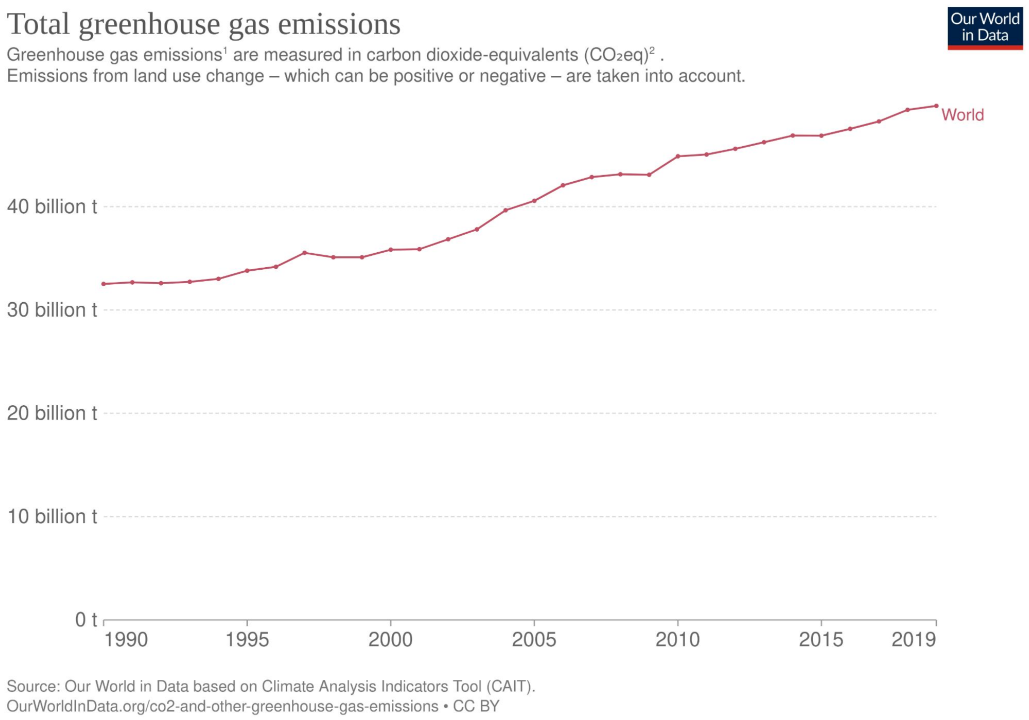




*water vapor has a timescale of only 9 days

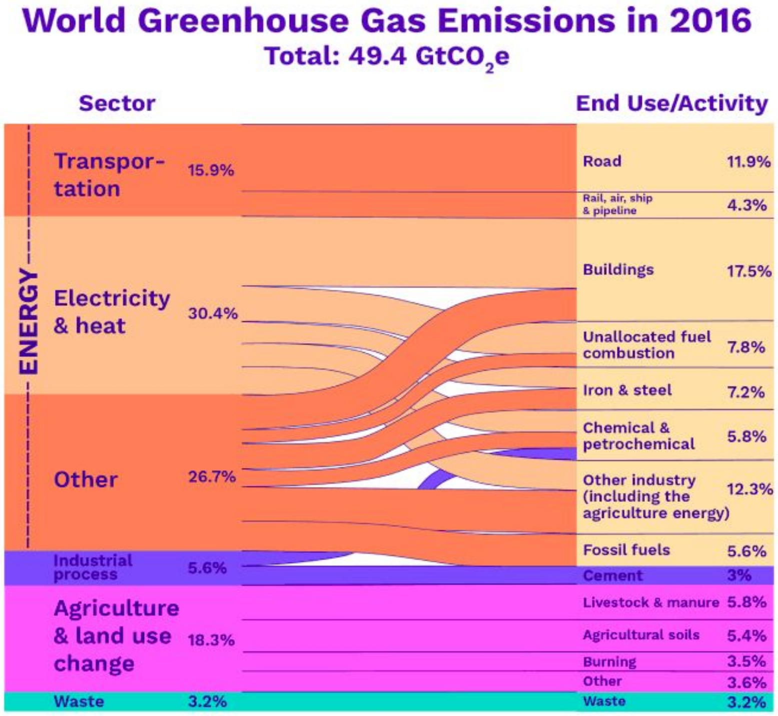
Different greenhouse gases have different "global warming potential". To account for this, total emissions are usually measured in "CO_2-equivalents"

Annual GHG emissions are increasing



But how do we measure this accurately? And why does it matter?

How can we measure the GHG emissions from all these different sources?



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

“Bottom-up” Approach

Amount of certain activity done or material produced	multiplied by	Average amount of emissions expected from that activity/production

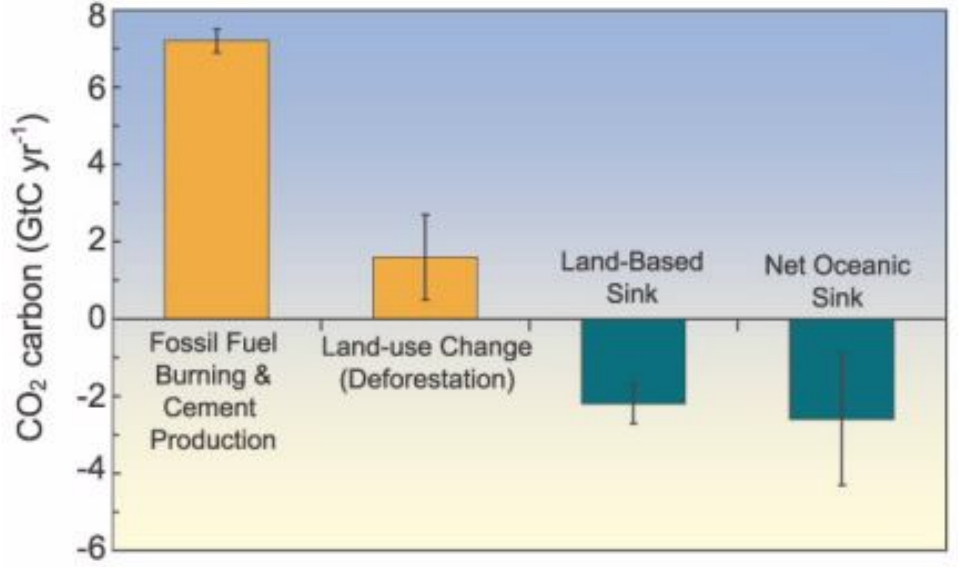
e.g.

100 tonnes of steel produced times 1.85 metric tons CO_2 per tonne of steel = 185 tons CO_2

Full calculations: https://www.pca.state.mn.us/business-with-us/greenhouse-gas-emissions-calculations

Includes sources and sinks

ACS:



International guidelines for the bottom up approach

2006 IPCC Guidelines for National Greenhouse Gas Inventories

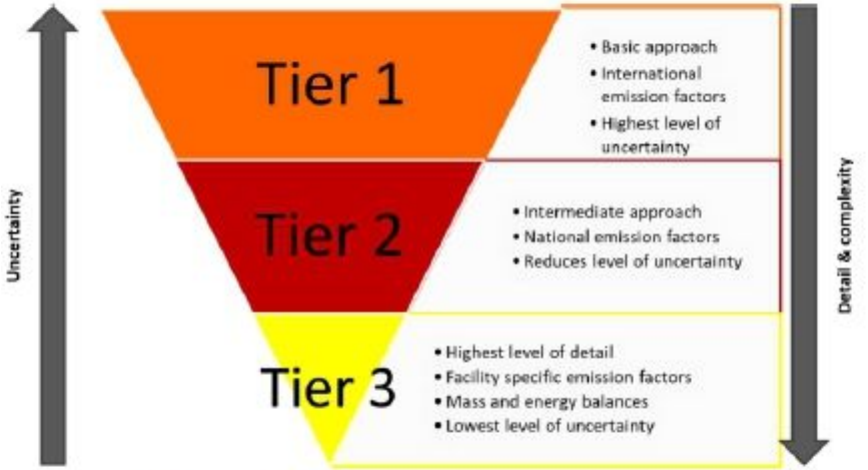


Figure 1: Different calculation methods [31]

IPCC guidelines for data difficulties

- **Filling gaps in periodic data:** Gaps in the time series will exist when data are available at less than annual frequency. For example, time consuming and expensive surveys relating to natural resources - such as national forest inventories - are compiled at intervals of every fifth or tenth year. Time series data may need to be inferred to compile a complete annual estimate for the years between surveys, and for fore- and back-casts (e.g., where estimates are needed for 1990 – 2004 and survey data are only available for 1995 and 2000). Chapter 5, Time Series Consistency, provides details on splicing and extrapolation methods to fill these gaps.
- **Time series revision:** In order to meet deadlines, statistical organisations may use modelling and assumptions to complete the most recent year of their estimates. These estimates are then refined the following year when all the data have been processed. Data may have been subject to further revision of historic data to correct errors or to update new methodologies. It is important that the inventory compiler look for these changes in the source data time series and integrate them into the inventory. Chapter 5 of this Volume contains more guidance on this issue.
- **Incorporating improved data:** While the ability of countries to collect data generally improves over time so they can implement higher tier methods, the data may not necessarily be suitable for earlier years for the higher tiers. For example when direct sampling and measurement programs are introduced there may be inconsistencies in the time series as the new program cannot measure past conditions. Sometimes this can be addressed if the new data are sufficiently detailed (e.g., if emission factors for modern abated plant can be distinguished from those of older unabated plant) and the historic activity data can be stratified using expert judgement or surrogate data. Chapter 5 provides more details on methods of incorporating improved data consistently across a time series.

IPCC guidelines for data difficulties

- **Compensating for deteriorating data:** Splicing techniques, as described in Chapter 5 on Time Series Consistency, can be used to manage data sets that have deteriorated over time. Deterioration can occur as the result of changing priorities within governments, economic restructuring, or diminishing resources. For example, some countries with economies in transition no longer collect certain data sets that were available in the base year, or these data sets may contain different definitions, classifications and levels of aggregation. The international data sources discussed in the activity data section (see Section 2.2.5) may provide another source of relevant activity data.
- **Incomplete coverage:** When data do not fully represent the whole country, e.g., measurements for 3 of 10 plants or survey data of the agricultural activity for 80 percent of the country, then the data can still be used but needs to be combined with other data to calculate a national estimate. In these cases expert judgement (see Section 2.2 above for details) or the combination of these data with other data sets (surrogate or exact data) can be used to calculate a national total. In some cases survey or census data are collected in a rolling national programme that samples different provinces or sub-sectors yearly with a repeat cycle that builds a complete data set after a period of years. It is recommended that, bearing in mind that time series consistency, assumptions made in one year must also apply to the other years, and that data providers be requested to compute representative yearly data with a complete coverage.

“Top down” approach

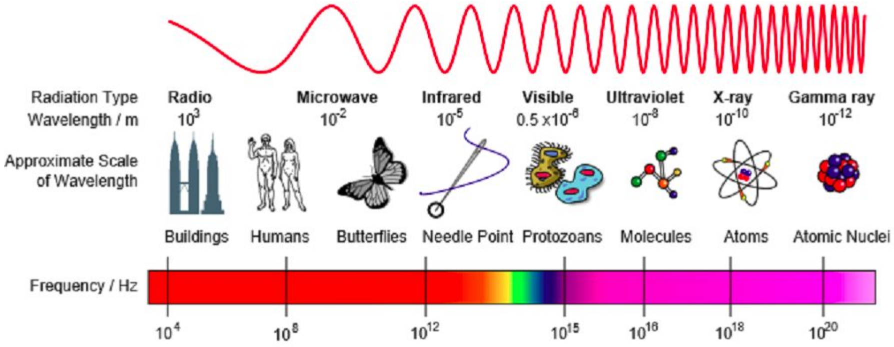
- Measure emissions directly, rather than relying on estimates based on activities
- Recent technological shifts have made this more feasible, on a local and global scale

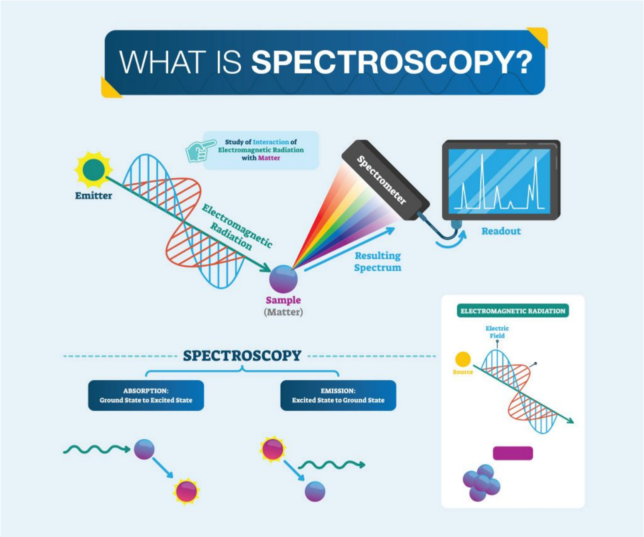
Spectroscopy

"To study the makeup of the atmosphere, scientists collect some air in a container and then shine what looks like a laser through the sample. When measuring the heat-trapping greenhouse gases that are causing climate change, such as carbon dioxide and methane, the "laser's" beam is made of infrared light, which has a slightly longer wavelength than the visible light our eyes can see.

"The reason these are greenhouse gases is [because they absorb infrared](),” Kroll says, meaning they trap heat energy that would otherwise leave the Earth as infrared light. “And you can use that absorption to measure them.”

"



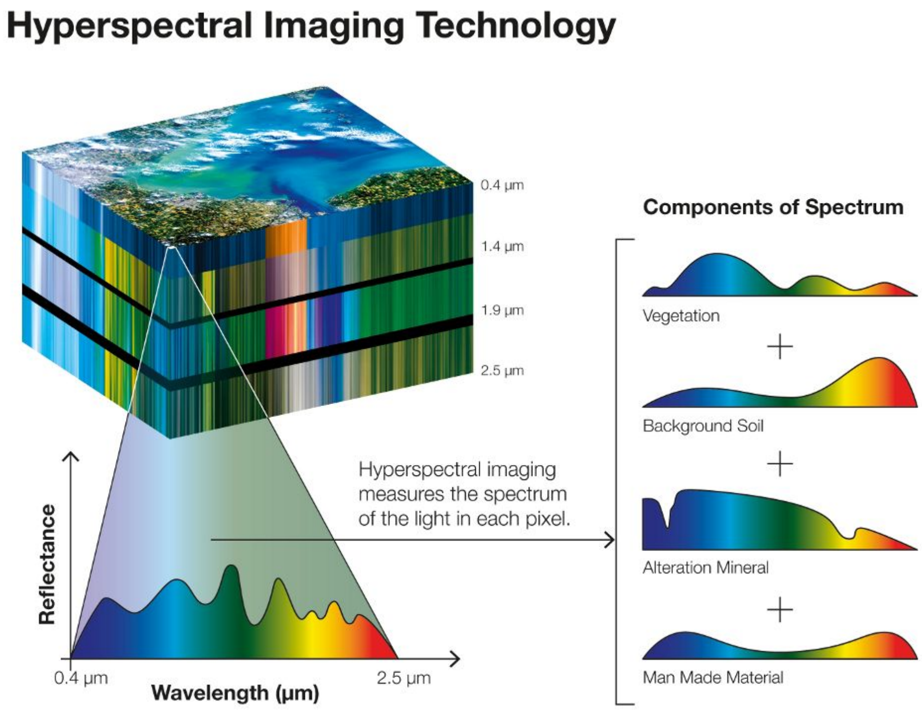


https://climate.mit.edu/ask-mit/how-are-gases-atmosphere-analyzed-and-measured

Remote Sensing

“Hyperspectral” satellites

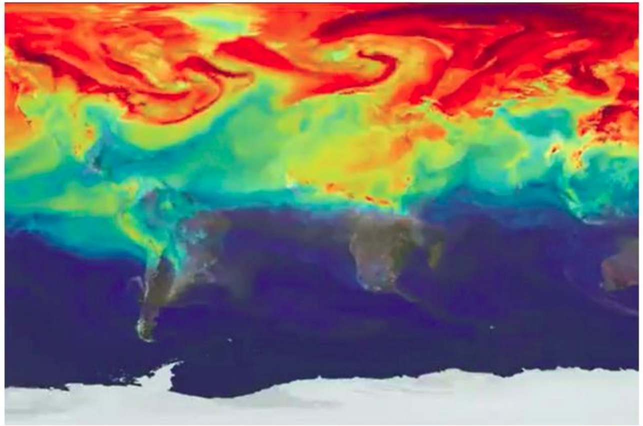
Collect data across many wavelengths, making it possible to do remote spectroscopy.



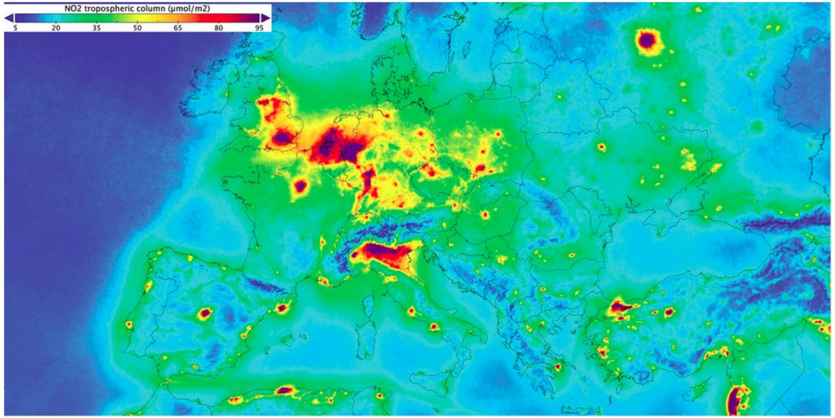
Eye from the Sky: Satellites to pinpoint greenhouse emissions and air pollution

By **Aditya Chaturvedi** - 07/29/2019 9 Minutes Read

Technological advancements like miniaturization of sensors, high-speed data transfer, and enhanced storage capabilities have led to a new wave of satellites specially built for tracking pollution and pinpointing sources of emissions.



NASA image shows how carbon dioxide shifts



According to the Air Quality in Europe report published in 2018 by the European Environment Agency (EEA), 19 EU Member States recorded nitrogen dioxide concentration above the annual permissible limit. Imagery from Sentinel-5P

Pros and Cons of Bottom up and Top Down

So which is better, bottom-up or top-down estimates?

- *A bottom-up estimate can provide significant insight into the specific source of emissions and importantly what specific actions can be taken to reduce emissions.*
- *A top-down estimate can provide insight on unexpected and in many cases very significant leaks, which cannot be identified from a bottom-up approach.*
- *A bottom-up estimate is more likely to take into account long-term conditions and variations, rather than a top-down "snapshot" in time.*
- *A top-down estimate can give an accurate snapshot of emissions which might be missed by incorrect assumptions in a bottom-up approach.*

Do both methods produce the same answer?

The global SF_6 source inferred from long-term high precision atmospheric measurements and its comparison with emission inventories

I. Levin[1], T. Naegler[1], R. Heinz[1], D. Osusko[1], E. Cuevas[2], A. Engel[3], J. Ilmberger[1], R. L. Langenfelds[4], B. Neininger[5], C. v. Rohden[1], L. P. Steele[4], R. Weller[6], D. E. Worthy[7], and S. A. Zimov[8]

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[7]Environment Canada, Climate Research Division/CCMR, 4905 Dufferin St., Toronto, ON M3H 5T4, Canada
[8]North East Section of the Russian Academy of Sciences, P.O. Box 18, Cherskii, Republic of Sakha (Yakutia), Russia

Received: 01 Dec 2009 – Discussion started: 11 Dec 2009 – Revised: 05 Mar 2010 – Accepted: 08 Mar 2010 – Published: 18 Mar 2010

Abstract. Emissions of sulphur hexafluoride (SF_6), one of the strongest greenhouse gases on a per molecule basis, are targeted to be collectively reduced under the Kyoto Protocol. Because of its long atmospheric lifetime (estimated as 800 to 3200 years), the accumulation of SF_6 in the atmosphere is a direct measure of its global emissions. Examination of our extended data set of globally distributed high-precision SF_6 observations shows an increase in SF_6 abundance from near zero in the 1970s to a global mean of 6.7 ppt by the end of 2008. In-depth evaluation of our long-term data records shows that the global source of SF_6 decreased after 1995, most likely due to SF_6 emission reductions in industrialised countries, but increased again after 1998. By subtracting those emissions reported by Annex I countries to the United Nations Framework Convention of Climatic Change (UNFCCC) from our observation-inferred SF_6 source leaves a surprisingly large gap of more than 70–80% of non-reported SF_6 emissions in the last decade. This suggests a strong under-estimation of emissions in Annex I countries and underlines the urgent need for independent atmospheric verification of greenhouse gases emissions accounting.

A review of bottom-up and top-down emission estimates of hydrofluorocarbons (HFCs) in different parts of the world

Hannah Flerlage [a] [1], Guus J.M. Velders [b] [c], Jacob de Boer [a]

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https://doi.org/10.1016/j.chemosphere.2021.131208   Get rights and content

Highlights

- Widening gap between global top-down derived and reported HFC emissions is explored.
- Data inaccessibility and inaccurate emission factors challenge bottom-up assessment.
- Non-uniform geographic domains in top-down studies hinder comparison.
- Availability of data and measurement station coverage are globally very different.

Generally, no.

Best methods will require a mix of both

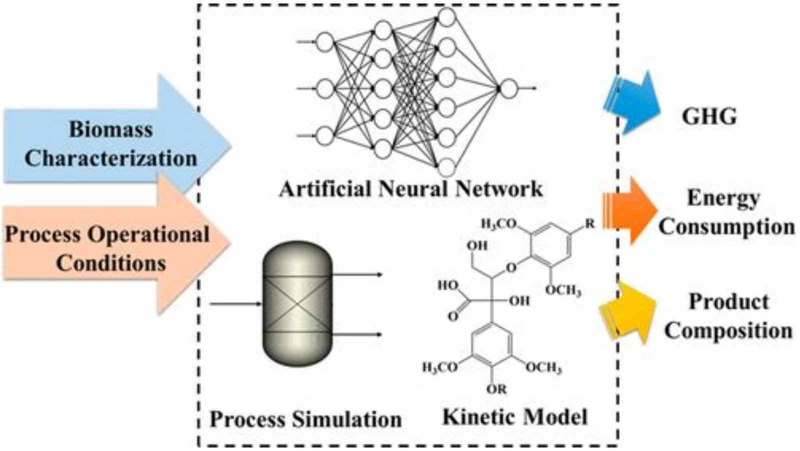
- Knowing the emissions multiplier for different activities requires direct measurement at some point
- Remote sensing can help to measure activities even if it can't always measure emissions directly

ML opportunities in measuring emissions

Filling in gaps for bottom up estimates

Abstract

Understanding the environmental implications of activated carbon (AC) produced from diverse biomass feedstocks is critical for biomass screening and process optimization for sustainability. Many studies have developed Life Cycle Assessment (LCA) for biomass-derived AC. However, most of them either focused on individual biomass species with differing process conditions or compared multiple biomass feedstocks without investigating the impacts of feedstocks and process variations. Developing LCA for AC from diverse biomass is time-consuming and challenging due to the lack of process data (e.g., energy and mass balance). This study addresses these knowledge gaps by developing a modeling framework that integrates artificial neural network (ANN), a machine learning approach, and kinetic-based process simulation. The integrated framework is able to generate Life Cycle Inventory data of AC produced from 73 different types of woody biomass with 250 characterization data samples. The results show large variations in energy consumption and GHG emissions across different biomass species (43.4–277 MJ/kg AC and 3.96–22.0 kg CO_2-eq/kg AC). The sensitivity analysis indicates that biomass composition (e.g., hydrogen and oxygen content) and process operational conditions (e.g., activation temperature) have large impacts on energy consumption and GHG emissions associated with AC production.



https://pubs.acs.org/doi/full/10.1021/acsuschemeng.9b06522

ML opportunities in measuring emissions

Making bottom-up estimates more precise

RESEARCH AND ANALYSIS | Open Access

Machine learning based modeling of households: A regionalized bottom-up approach to investigate consumption-induced environmental impacts

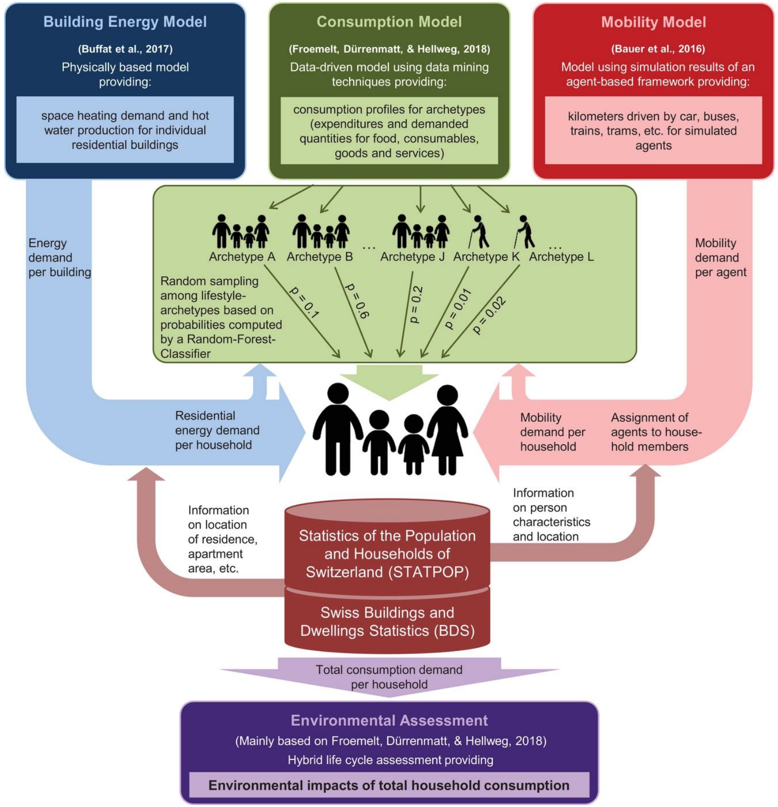
Andreas Froemelt, René Buffat, Stefanie Hellweg

First published: 24 November 2019 | https://doi.org/10.1111/jiec.12969 | Citations: 25

Funding information:

This research project is financially supported by the Swiss Innovation Agency Innosuisse and is part of the Swiss Competence Centers for Energy Research SCCER Mobility and FURIES (Future Swiss Electrical Infrastructure). Further funding has been provided by the Swiss National Science Foundation (SNSF grant number: P2EZP2_184267).

Editor Managing Review: Richard Wood



https://pubs.acs.org/doi/full/10.1021/acssuschemeng.9b06522

ML opportunities in measuring emissions

Using novel data sources to estimate energy/activity

Webcrawling and machine learning as a new approach for the spatial distribution of atmospheric emissions

Susana Lopez-Aparicio, Henrik Grythe, Matthias Vogt, Matthew Pierce, Islen Vallejo

Published: July 16, 2018 • https://doi.org/10.1371/journal.pone.0200650

Abstract

In this study we apply two methods for data collection that are relatively new in the field of atmospheric science. The two developed methods are designed to collect essential geo-localized information to be used as input data for a high resolution emission inventory for residential wood combustion (RWC). The first method is a webcrawler that extracts openly online available real estate data in a systematic way, and thereafter structures them for analysis. The webcrawler reads online Norwegian real estate advertisements and it collects the geo-position of the dwellings. Dwellings are classified according to the type (e.g., apartment, detached house) they belong to and the heating systems they are equipped with. The second method is a model trained for image recognition and classification based on machine learning techniques. The images from the real estate advertisements are collected and processed to identify wood burning installations, which are automatically classified according to the three classes used in official statistics, i.e., open fireplaces, stoves produced before 1998 and stoves produced after 1998. The model recognizes and classifies the wood appliances with a precision of 81%, 85% and 91% for open fireplaces, old stoves and new stoves, respectively. Emission factors are heavily dependent on technology and this information is therefore essential for determining accurate emissions. The collected data are compared with existing information from the statistical register at county and national level in Norway. The comparison shows good agreement for the proportion of residential heating systems between the webcrawled data and the official statistics. The high resolution and level of detail of the extracted data show the value of open data to improve emission inventories. With the increased amount and availability of data, the techniques presented here add significant value to emission accuracy and potential applications should also be considered across all emission sectors.

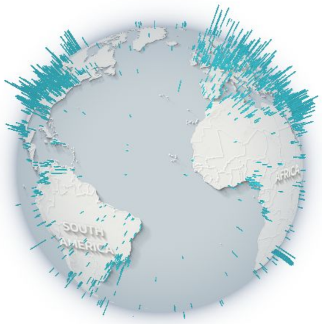
ML opportunities in measuring emissions

Analyzing satellite images to track activity and directly measure emissions

CLIMATE TRACE

INDEPENDENT GREENHOUSE
GAS EMISSIONS TRACKING

EXPLORE THE MAP »   DOWNLOAD THE DATA »



Using satellites, direct measurements, and artificial intelligence, we build models that estimate emissions right at the source.

Paper Deep Dive

Detecting Methane Plumes using PRISMA: Deep Learning Model and Data Augmentation

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https://arxiv.org/pdf/2211.15429.pdf

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?

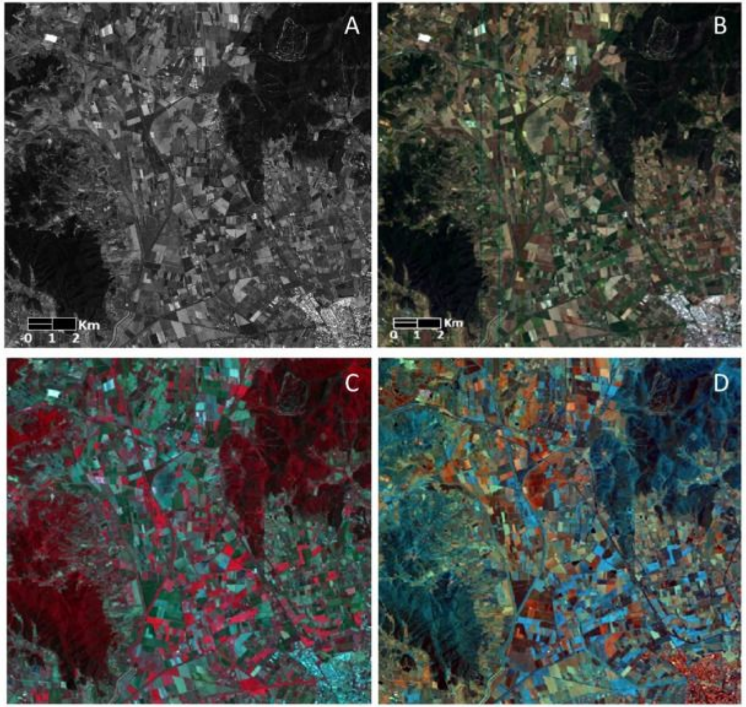
If successful, how could this system be useful?

Abstract

The new generation of hyperspectral imagers, such as PRISMA, has improved significantly our detection capability of methane (CH_4) plumes from space at high spatial resolution ($\sim$30m). We present here a complete framework to identify CH_4 plumes using images from the PRISMA satellite mission and a deep learning model able to detect plumes over large areas. To compensate for the relative scarcity of PRISMA images, we trained our model by transposing high resolution plumes from Sentinel-2 to PRISMA. Our methodology thus avoids computationally expensive synthetic plume generation from Large Eddy Simulations by generating a broad and realistic training database, and paves the way for large-scale detection of methane plumes using future hyperspectral sensors (EnMAP, EMIT, CarbonMapper).

PRISMA satelitte

Looking in different spectral bands:



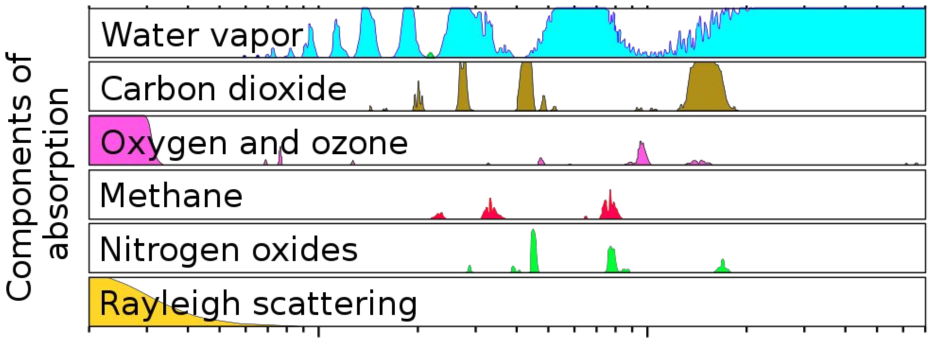
- Launched on March 22nd, 2019 by the Italian Space Agency
- Hosts a high-resolution spectrometer and a camera
- Intended uses: topsoil measurements, mapping of raw materials, forest resources and ecosystem biodiversity assessment, agricultural crop monitoring, snow and ice surface property mapping and inland/coastal water quality assessment, etc.

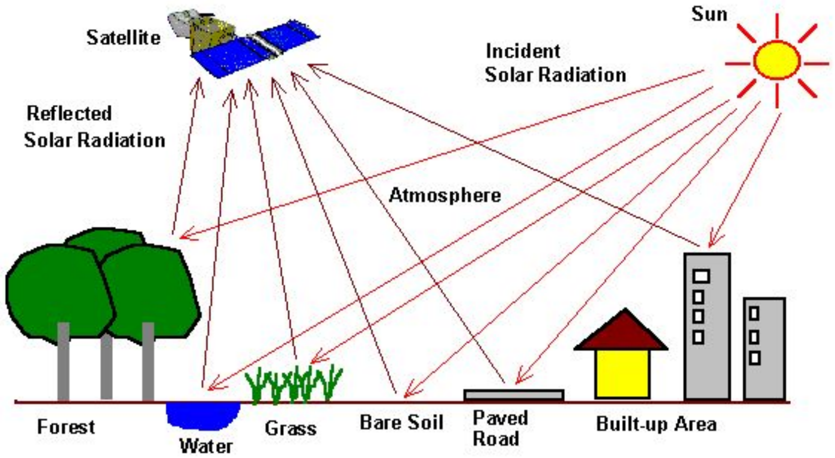
https://www.sciencedirect.com/science/article/pii/S0034425721002170

Methane detection

PRISMA has good shortwave infrared (1 to 2.5μm) coverage, which is where methane absorption is significant.

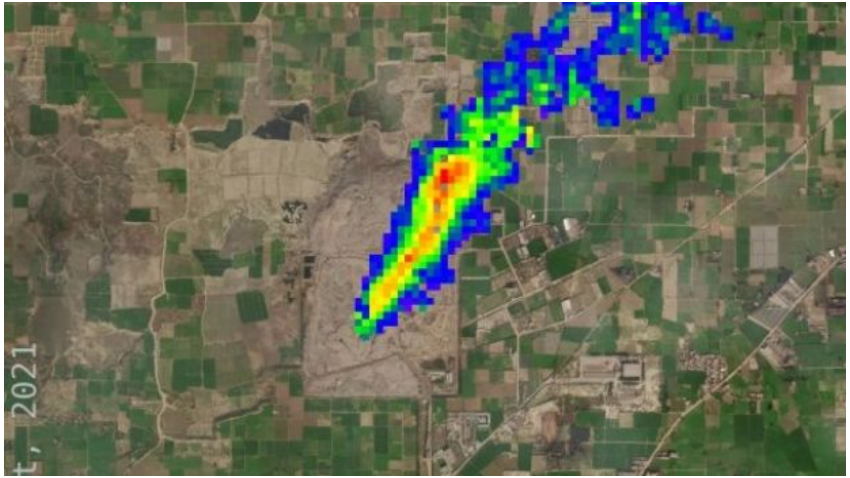
By knowing the radiative properties of methane, the concentration of it in the column of atmosphere between the satellite's sensor and a pixel on the ground can be calculated.





Methane plumes

- Large methane clouds released from a single source
- Come from oil and gas operations, landfills, etc.
- Potent polluters and easier to detect and respond to than more diffuse sources



Methane plume over Lakhodair landfill in Lahore, Pakistan, spotted on July 1, 2021. , GHGSat/Bloomberg

Goal

- Do image segmentation to detect and determine the extent of a plume

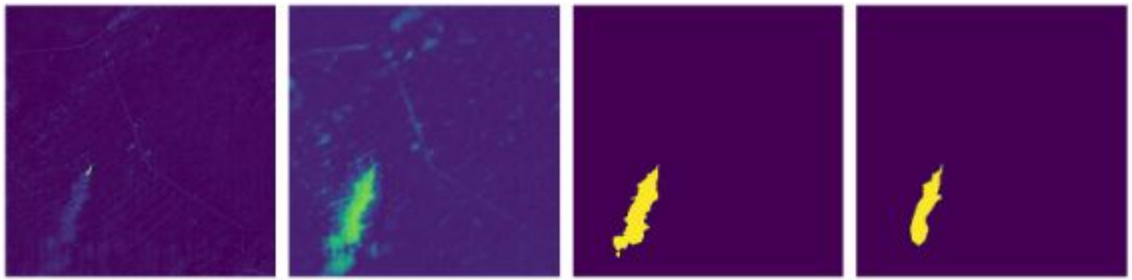
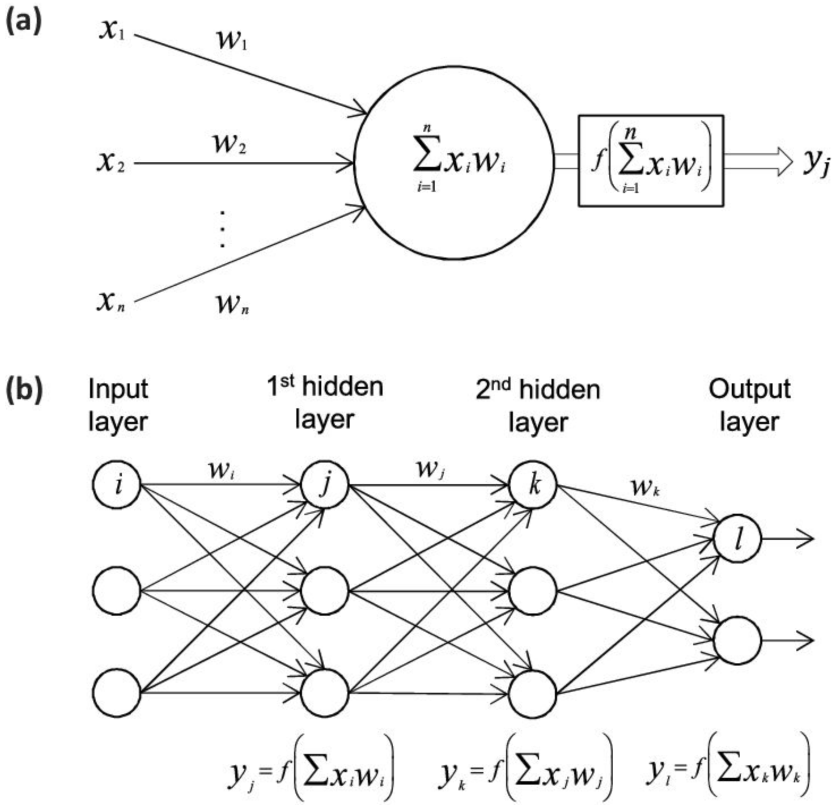
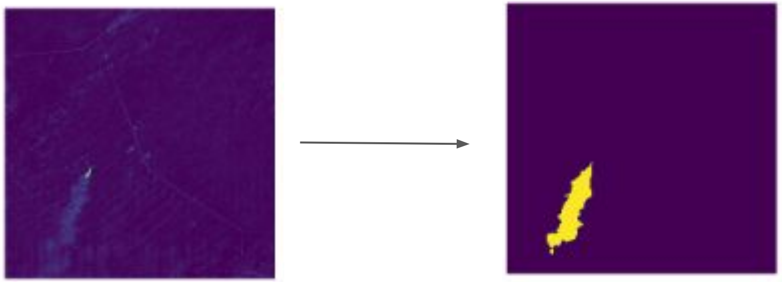


Figure 1: Examples of automatically-detected XCH_4 plumes including XCH_4 concentration maps (left column), the probability map predicted by the network (second column), hysteresis thresholding (third column), and manually labeled ground truth (right column)

Method



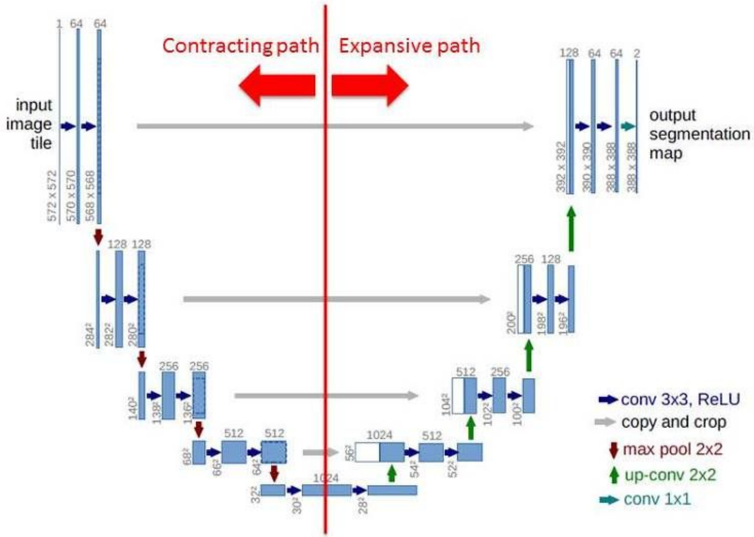
Artificial neural network that takes in an image of methane concentration and outputs a binary image of plume/not plume.



Vieira et al.

Method

Network Architecture



2.3.2 Model

The detection step is performed using a U-Net architecture, which is one of the most popular architecture for segmentation [14]. The network is designed to predict a probability map by applying a normalized exponential function (softmax) activation to the output of the final convolutional layer. Each pixel is thus assigned a probability of belonging to a XCH_4 plume. This map is then converted into a binary mask by applying a hysteresis thresholding with a low threshold and a large threshold. This approach allows us to detect the whole plume and not only the area close to the source exhibiting the highest XCH_4 concentrations. In order to validate the artificial plume generation technique, we

Data problem!

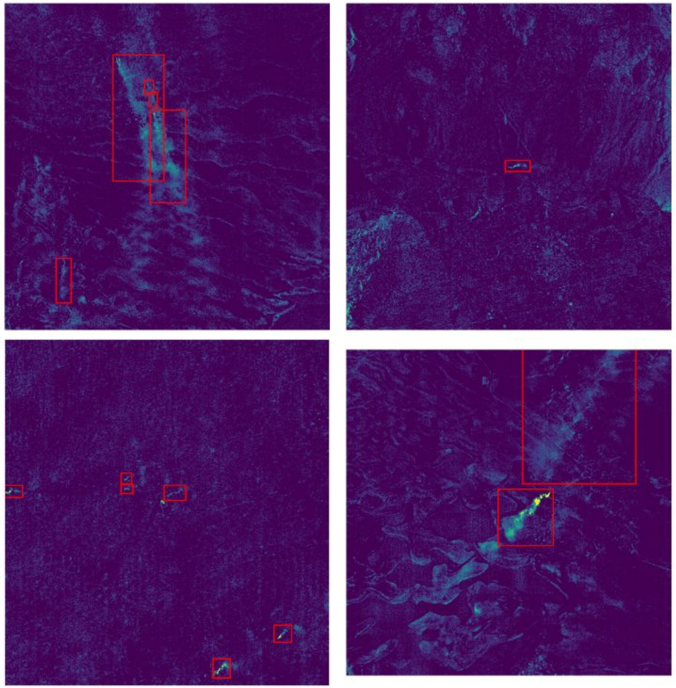
PRISMA is new and hasn't released very many images yet, especially ones that contain methane plumes. Deep neural networks need a lot of data to learn all their parameters!

"Our study is based on 40 PRISMA images containing a total of 75 plumes of methane. This hardly describes the great diversity of plumes (i.e. size, intensity, morphology) and associated background (e.g. different levels of homogeneity, variable amount of noise, presence of clouds, roads, or buildings, types of terrain)."

Data problem!

Methane plumes can be diverse and other things in the atmosphere/ground can look like methane.

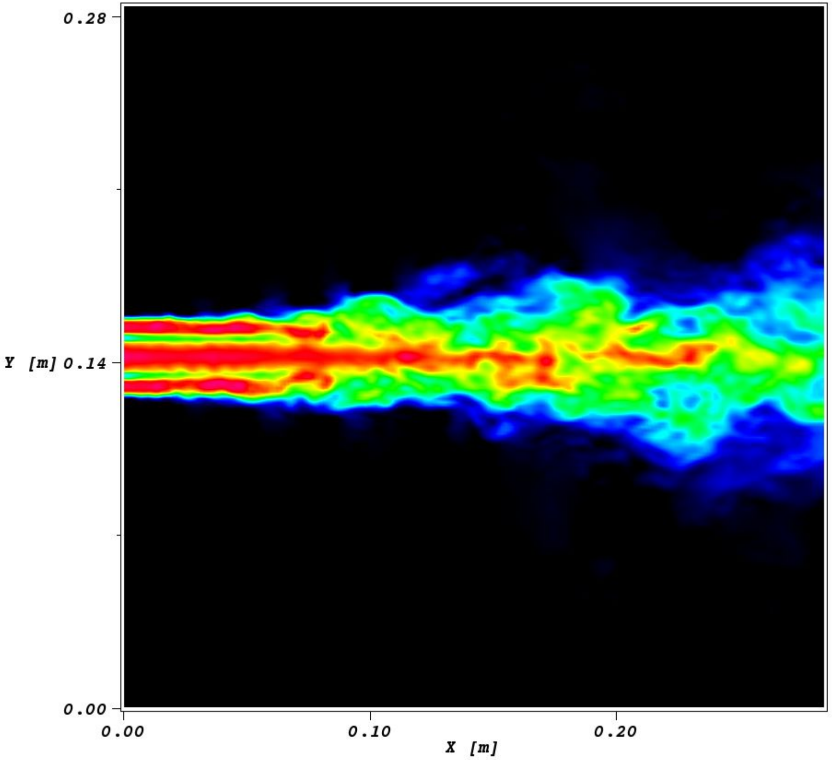
“We also observe the presence of false positives in the retrieval results. False positives are elements in the scene with a high response but do not correspond to higher XCH4 concentrations. False positives are caused by aerosols or heterogeneous surface properties with strong spectral signatures [15] similar to methane, such as hydrocarbon paints on buildings or roads, mountain ridges/slopes or sand dunes.”



Solutions

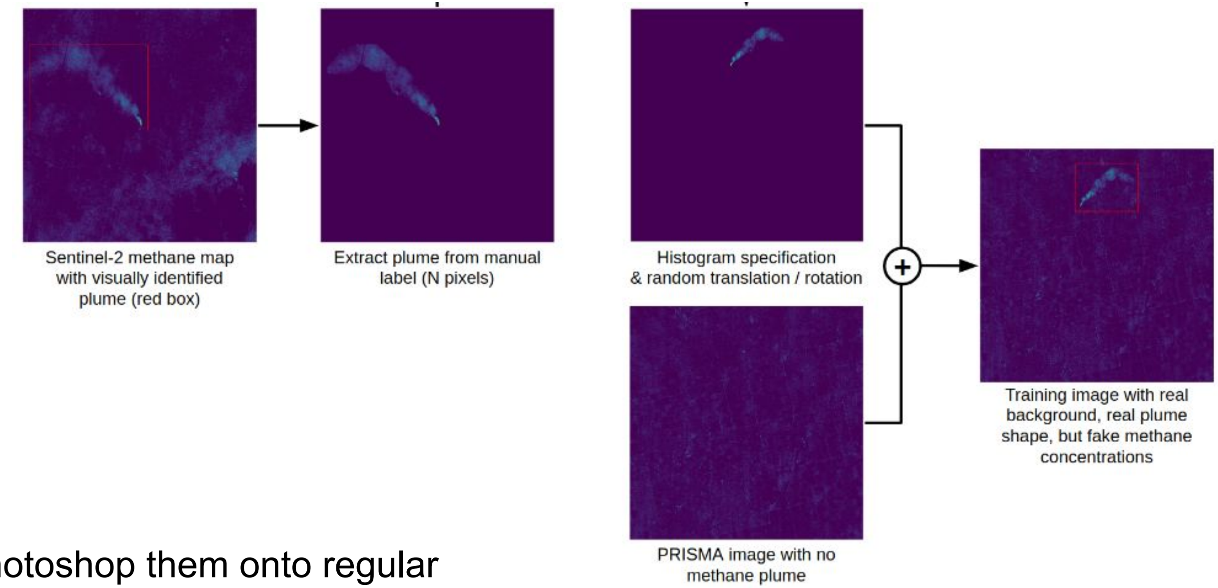
- Train on simulated data?

  "Gaussian plume simulations rely on a simple modelling of gas dispersion, but the final plume has a relatively naive shape, not representative of complex spatial structures observed from space. To simulate more complex structures, Large Eddy Simulations (LES) rely on an accurate physical modelling of the atmospheric dispersion and turbulence to generate realistic plumes. **But these models remain computationally expensive**"



Solutions

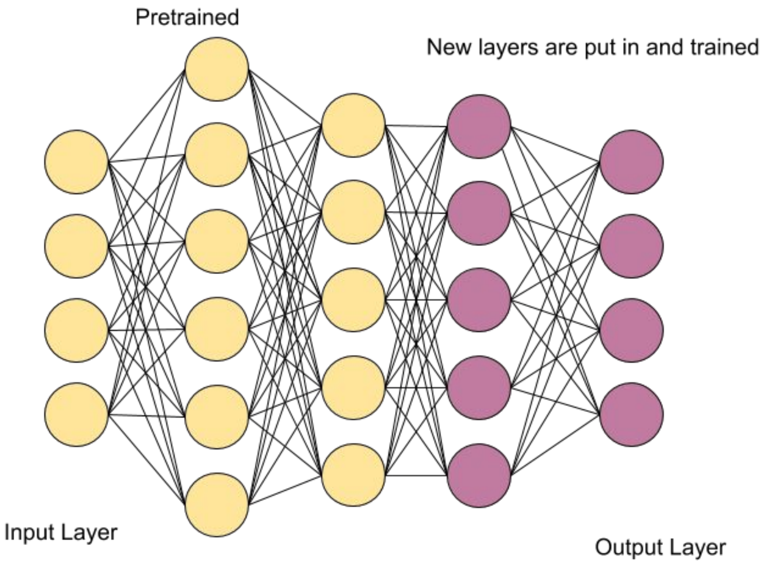
- Train on plumes seen from a different (less good) satellite:



(essentially photoshop them onto regular PRISMA images)

Solutions

- Train a full model using data from another satellite, then train further on PRISMA images:



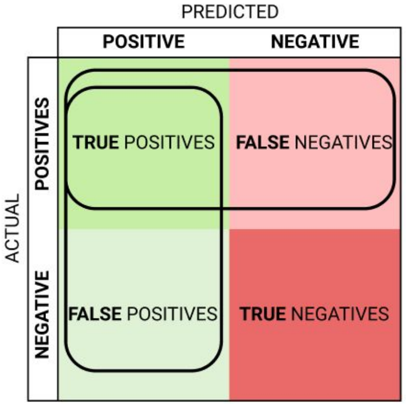
"Transfer" learning

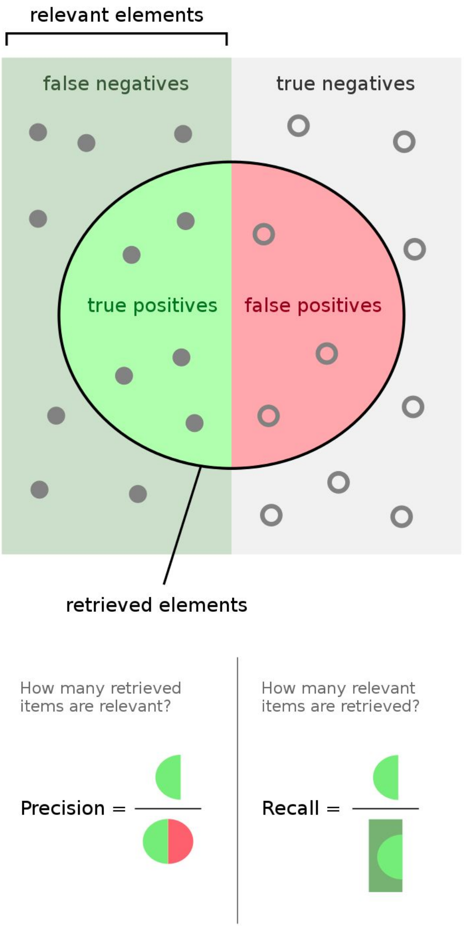
Evaluation

- Precision
- Recall

F1-score

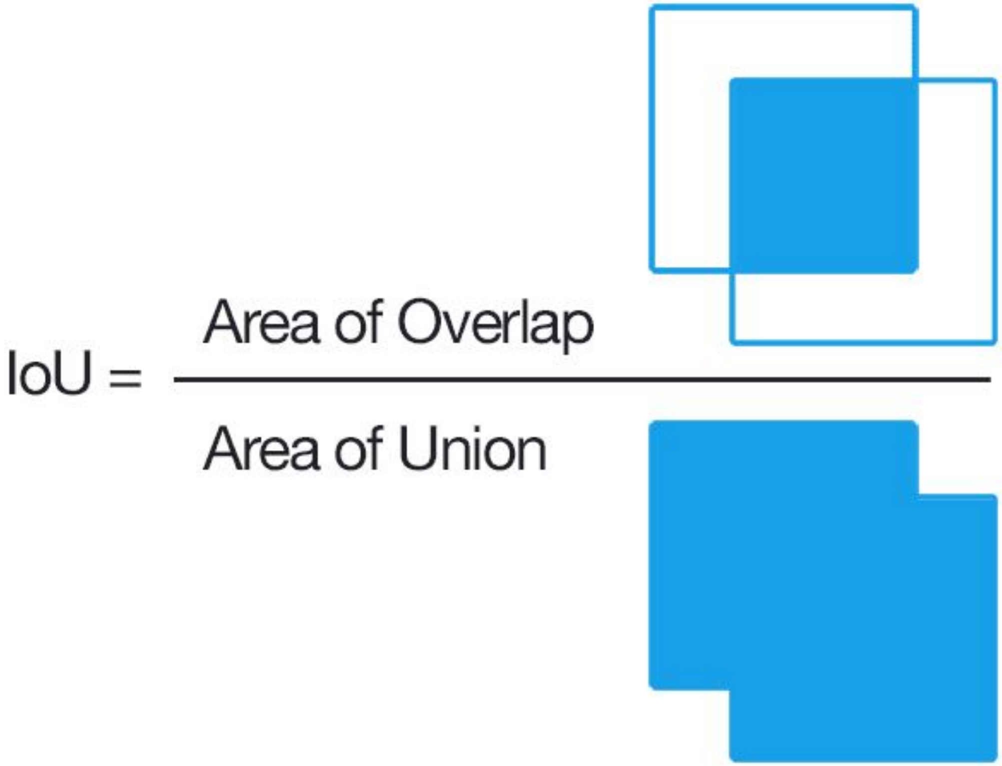
$$2\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$





Evaluation

- Intersection Over Union (IoU)
- 1 is best



PyImageSearch

Results

Results

Table 1: Models performance comparison for automatic methane plume detection

	detection metrics			segmentation metrics	
	precision	recall	f1-score	IoU	mIoU
Transfer Learning	0.28	0.53	0.37	0.21	0.13
Plumes Transfer	0.88	0.42	0.57	0.61	0.19

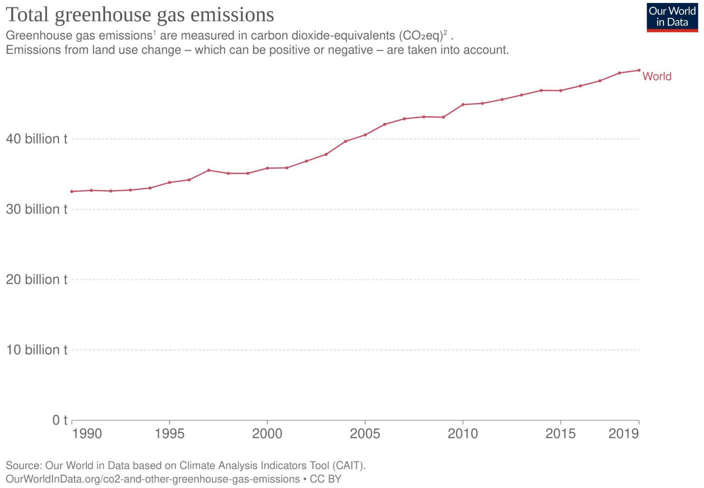
In table 1, we make a quantitative comparison between the performance of the model trained from scratch on artificial data, and the model obtained by transfer learning from pre-trained weights learnt on Sentinel-2 images. For both approaches, we consider the hysteresis thresholds producing the best IoU. The detection metrics are computed on a mask basis, a mask being considered a true positive if it intersects a ground-truth mask. The model trained from scratch on synthetic plumes outperforms the model by transfer learning on both the detection and segmentation tasks. The latter notably detects a large number of false positives, leading to a poor precision and IoU even if it reaches a slightly better recall. We also observe a drop when passing from the IoU to the mean IoU (mIoU), which can be explained by the fact that the model often fails to detect the smallest plumes.

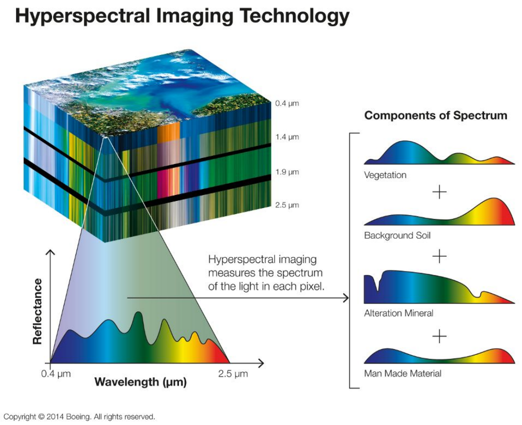
Using the photoshopped images was best!

Conclusion

In this study, we presented a full processing pipeline for the identification of methane plumes in hyperspectral images from PRISMA. It makes use of classic methods for the spectral recalibration and methane concentrations retrieval. We also propose an automatic detection approach based on a CNN that is trained from scratch using a plume transfer method to generate training samples from methane plumes in Sentinel-2 images. This novel approach allows to train a dedicated model for a new remote sensing technology, while mostly relying on data from previous satellites.

Summary





2006 IPCC Guidelines for National Greenhouse Gas Inventories

Detecting Methane Plumes using PRISMA: Deep Learning Model and Data Augmentation