

ML4CC: Lecture 6

Sit with your discussion groups (same as last time)!

Assignments reminder

Keep doing your weekly PMIRO+Q

Your second coding assignment was due **today** before the start of class.

You have an exam on **March 6th (8am)**

Recap of previous paper

P: No way to say if 2 atmospheric states are “similar”

M: Use self-supervised learning (temporal difference prediction) to learn representation of atmospheric states, and use this representation as the basis of a distance metric (AtmoDist)

I: Self-supervised learning for this problem

R: AtmoDist behaves intuitively and better than image-based losses in tasks such as super-resolution

O: Does this definition of similarity capture what matters for climate models (e.g. physical laws)?

Climate Change in the News

≡ CNN Climate Solutions Weather

👁 Watch 🗣 Listen 🔴

Trump bars federal scientists from working on pivotal global climate report



By Ella Nilsen and Laura Paddison, CNN

🕒 2 minute read · Updated 6:38 PM EST, Fri February 21, 2025

(CNN) — The Trump administration told US government scientists working on a vital global climate report to stop their work, according to a scientist involved in the report – the latest move to withdraw the US from global climate action and research.

The US had been highly involved in planning for the next installment of the report due out in 2029 from the Intergovernmental Panel on Climate Change, the world's leading scientific authority on climate change.

The IPCC assesses how the climate crisis is affecting the planet according to the latest science. Its reports take thousands of scientists many years to produce and are used to inform policymakers across the world of the risks posed by global warming.

In a sense, all of the world's current, accepted knowledge about climate change stems from the IPCC and its reports, the first of which was published in 1990.

An international meeting of IPCC authors that was scheduled to take place in China next week is now in limbo. Kate Calvin, NASA's chief scientist and senior climate advisor, was supposed to co-chair the discussion but was impacted by the stop-work order, according to the scientist involved in the report. The meeting was planned to talk about next steps in the development of the report.

"Dr. Calvin will not be traveling to this meeting," a NASA spokesperson said. NASA denied CNN's request for an interview with Calvin.

The person involved in the report told CNN they were "not sure what this means for the planned work going forward, or if US scientists will participate in the writing of the IPCC reports."

"The IPCC is the backbone of global climate science, providing the world with unbiased, evidence-based insights needed to confront the climate crisis," said Harjeet Singh, a climate advocate and founding director of Satat Sampada Climate Foundation.

"The decision to exclude US scientists significantly undermines this collaborative effort and risks compromising the process at a time when robust climate action is needed more than ever," he told CNN in a statement.

Climate Change in the News

Grist

Donate

The Counter

Rice paddies, like cows, spew methane. A new variety makes them a lot less gassy.

Rice plants are a big source of methane, an extremely potent greenhouse gas. Scientists just developed a strain that cuts those emissions by 70 percent.



In this new study, researchers led by Schnürer and Yunkai Jin, a plant biologist at China's Hunan Agricultural University, compared a non-genetically-modified cultivar of rice, which had average methane emissions, and a genetically modified variety with low emissions. They found that the engineered strain produced significantly less fumarate, an organic compound. And the less fumarate the plants were secreting, the fewer methanogens living in the soil.

The researchers also discovered that the low-methane GMO rice released much more ethanol, an alcohol. When they applied ethanol to soils where rice plants were growing, that alone reduced methane emissions. "That turned out to be an inhibitor for the methanogens," Schnürer said. "So it was two factors: Both fumarate and ethanol play a role in the reduction of methane." They also applied another chemical, oxantel, to the soils, which significantly reduced methane emissions as well.

Paper 5 Discussion

IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 60, 2022

Semantic Segmentation Based on Temporal Features: Learning of Temporal–Spatial Information From Time-Series SAR Images for Paddy Rice Mapping

Lingbo Yang¹⁰, Ran Huang¹⁰, Jingfeng Huang¹⁰, Tao Lin, Limin Wang, Ruzemaimaiti Mijiti,
Pengliang Wei¹⁰, Chao Tang¹⁰, Jie Shao¹⁰, Qiangzi Li, and Xin Du¹⁰

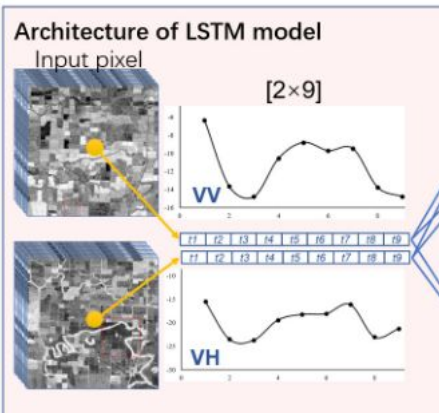
Attendance

Select one person from the group to be the attendance taker and fill out the attendance form (linked to under syllabus in Brightspace)

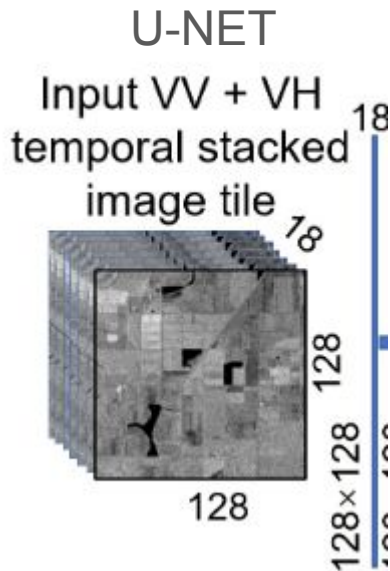
Discussion Question 1

The paper compares 4 different model. What is the same/different about how the input data fed into each of these models?

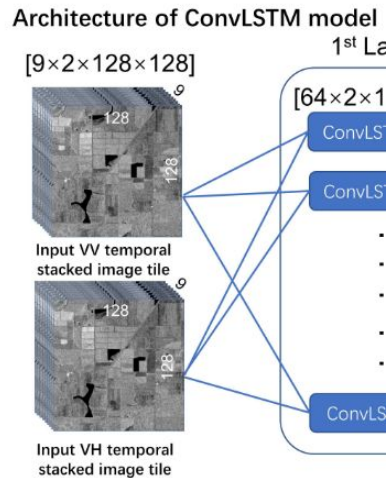
Input dimensions



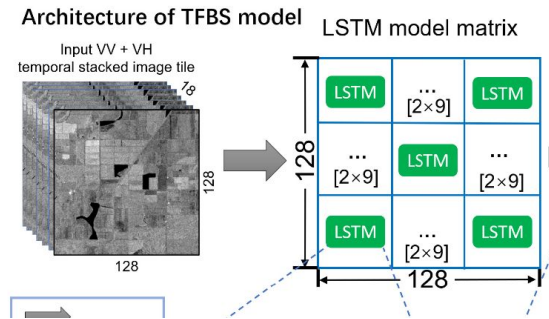
Time-series of two channels at a single location, passed in over 9 time steps.



128x128 spatial images concatenated across both channels and all 9 time steps



128x128 spatial images with 2 channels passed in over 9 time steps

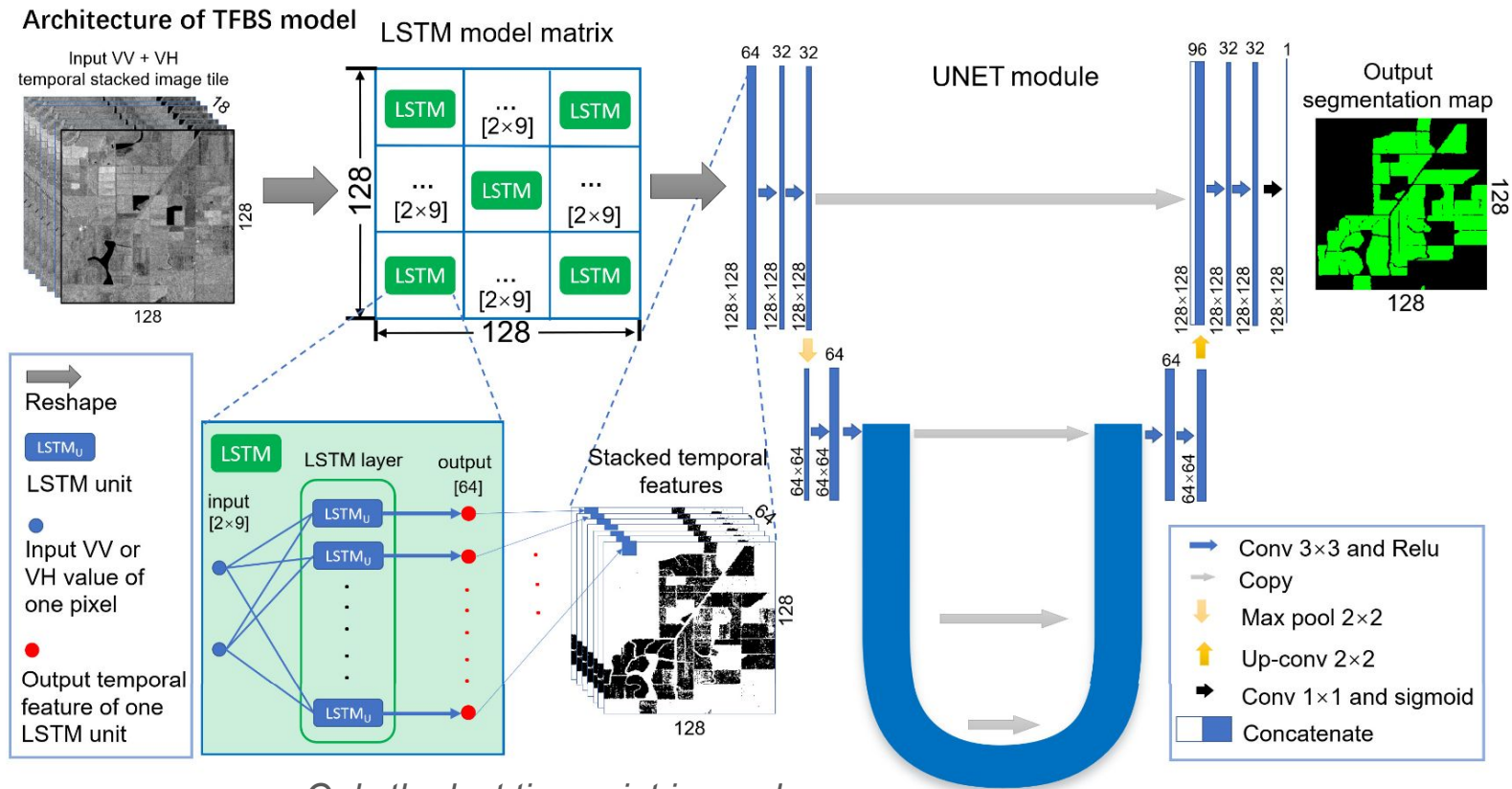


Each location in 128x128 image has 2 channels passed in over 9 time steps

Discussion Question 2

Describe the TFBS model architecture in your own terms. At what point does the model stop having temporal dynamics?

TFBS attaches pixelwise LSTMs to a U-Net



Only the last timepoint is used to create the input to the U-Net

Discussion Question 3

The paper tests 3 different types of generalization performance and one type of transfer learning. What are they and which figures show the results for each?

Within-distribution generalization

training process. The performances of the LSTM, UNET, ConvLSTM, and TFBS models are evaluated using datasets from ARMSMOTN in 2019, with 10-fold cross validation used as the evaluation method. This method randomly partitions the original dataset into ten equally sized subdatasets. Then, a single subdataset is retained as the validation dataset, and the remaining nine subdatasets are used as training data. This process is repeated ten times, with each of the ten subdatasets used exactly once as the validation dataset. A final estimation can then be calculated by averaging the ten results. The

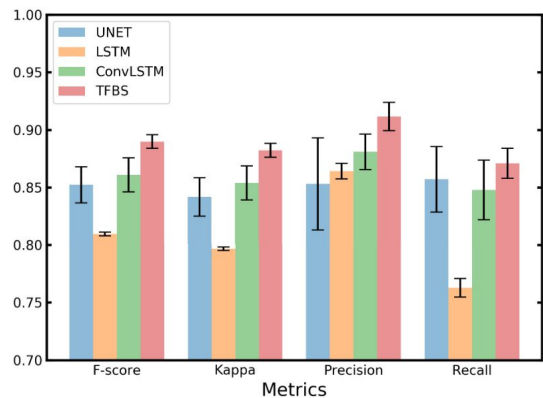


Fig. 7. Final result of the average F-score, kappa coefficient, precision, and recall of UNET, LSTM, TFBS, and ConvLSTM models, assessed by 10-fold cross validation method based on the dataset from ARMSMOTN in 2019. Error bars in the figure represent one standard deviation from the average accuracy.

Spatial and temporal generalization

The growth period of crops varies slightly because the climate conditions vary from place to place and year to year. Therefore, when the model trained in a specific year and place is applied to other years or other places, its accuracy in crop classification is affected by the temporal and spatial generalizability of the model. In this study, all the data from ARMSMOTN in 2019 were used to train four deep learning models. The datasets from ARMSMOTN in 2017 and 2018 were used to evaluate the temporal generalizability of the trained deep learning models. In addition, with a view to further testing the spatial-temporal generalizability of the deep learning models, the datasets from northern LA in 2017–2019 were used as validation data to test the deep learning models trained with the ARMSMOTN 2019 dataset.

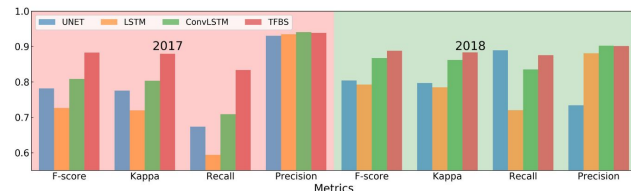
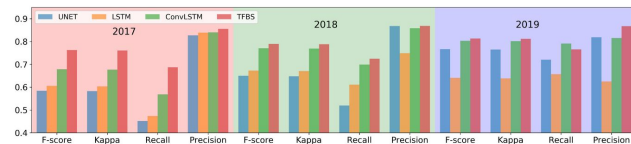


Fig. 10. Illustration of classification accuracies of UNET, LSTM, ConvLSTM, and TFBS models in 2017 (with red background) and 2018 (with green background). All the four models are trained with the ARMSMOTN dataset in 2019. CDL data is used as reference data to assess the accuracies.



Transfer learning

Besides, deep learning models which pretrained using the ARMSMOTN 2019 dataset are applied to the SV region for rice mapping. Due to the sowing date of rice in SV is relatively late than that in ARMSMOTN, it is not practical to map rice in SV by using the pretrained model directly. Therefore, fine-tuning method is employed to adapt pretrained models to new areas [80]. The parameters of the output layer for each pretrained deep learning model are initialized as zero, while the parameters of other layers are retained. An image tile with a spatial size of 128×128 pixels and its corresponding CDL image is randomly selected from the SV 2019 dataset. The selections are used to retrain the new output layer for each pretrained deep learning model. Based on the fine-tuned model, the rice classification results in the SV area from 2017 to 2019 are obtained, and the classification accuracy is evaluated by using CDL data as reference. In order to ensure

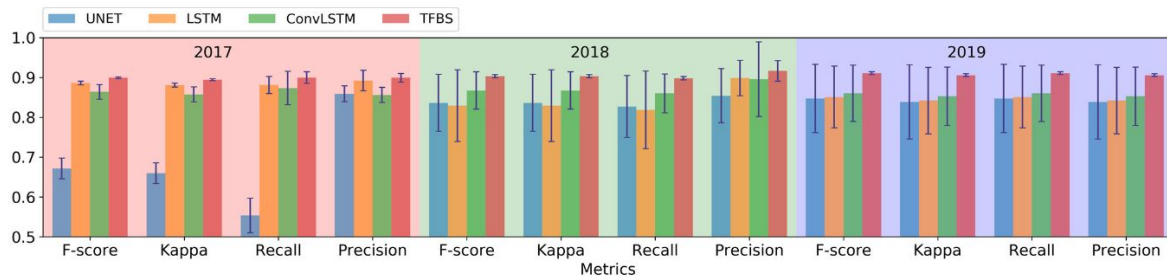


Fig. 13. Rice mapping accuracies of the fine-tuned deep learning models. The models were pretrained by ARMSMOTN 2019 dataset and transferred to SV based on fine-tuning technology. The CDL data of SV from 2017 to 2019 were used as reference data.

Discussion Question 4

What is data augmentation? What kind is done here? Does it help?

Making extra data

DATA AUGMENTATION

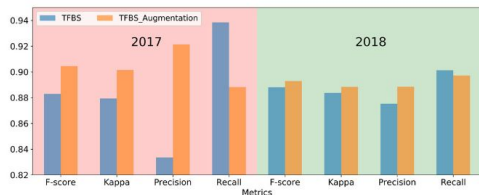


Fig. 15. Accuracies of TFBS models before (blue bars) and after data augmentation (orange bars). Dataset from ARMSMOTN in 2019 is used as training data, and the ARMSMOTN datasets from 2017 (red background) and 2018 (green background) are used as test data.

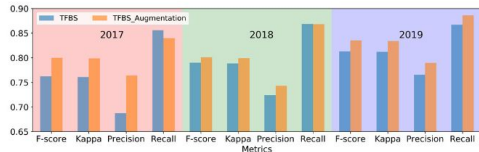
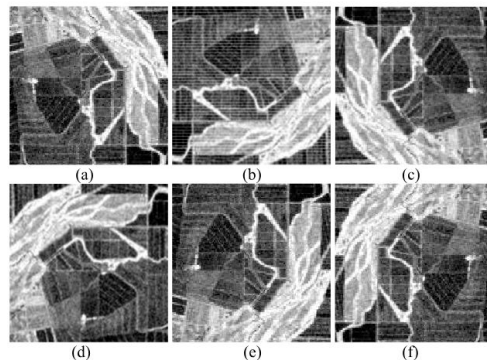


Fig. 16. Accuracies of TFBS models before (blue bars) and after data augmentation (orange bars). Dataset from ARMSMOTN in 2019 is used as training data, and the northern LA datasets from 2017 (red background), 2018 (green background), and 2019 (blue background) are used as test data.

Helps
a bit

Data augmentation is a useful technique to increase the amount and the diversity of the training data. The effects of data augmentation on the spatial and temporal generalizability of the TFBS model are evaluated in this study. Several augmentation techniques, including spatial augmentation (rotation and flipping) and temporal augmentation (random scaling of backscatter coefficient), are used to increase the size of the dataset from ARMSMOTN in 2019. The raw tile images are first randomly rotated 90° , 180° , or 270° clockwise [Fig. 6(b)–(d)]; then, the rotated images are multiplied by a random value between 0.9 and 1.1 to increase the fluctuation of the time-series curve of the sample data. In addition, each raw tile image is flipped vertically or horizontally [Fig. 6(e) and (f)], and the flipped image is subsequently multiplied by a random number between 0.9 and 1.1. Thus, the size of the training dataset is tripled.



Discussion Question 5

What is meant by 'stability' here? How is it measured and how is it plotted?

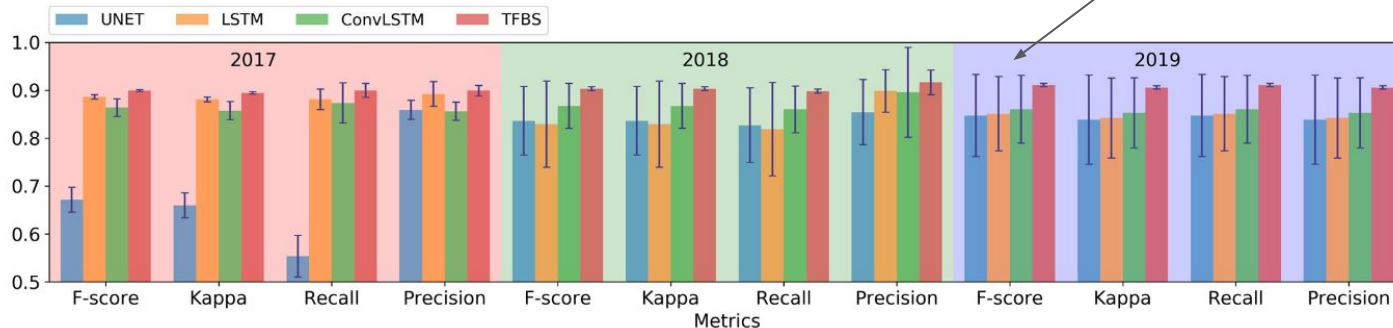
D. Rice Mapping Based on Fine-Tuned Deep Learning Models

Four deep learning models were pretrained by ARMSMOTN 2019 dataset and then applied to the SV based on fine-tuning method for rice mapping from 2017 to 2019. CDL data were used to evaluate the classification accuracy from each model. Fig. 13 shows that TFBS significantly outperforms UNET, LSTM, and ConvLSTM in all three years in SV's rice mapping, the average F-score of which is 15.2%, 5.7%, and 4.7% higher than that of UNET, LSTM, and ConvLSTM, respectively. Meanwhile, the stability of TFBS model is also higher than the other three of which shows a much lower standard deviation of classification accuracy. The results show that it is feasible to apply a pretrained model to areas with different rice phenology for rice mapping based on fine-tuning technology and a small number of samples.

Calculating means and standard deviations for processes that involve randomness

each pretrained deep learning model. Based on the fine-tuned model, the rice classification results in the SV area from 2017 to 2019 are obtained, and the classification accuracy is evaluated by using CDL data as reference. In order to ensure the reliability of the results and the stability evaluation of the fine-tuning for each model, this process was repeated ten times. The mean and standard deviation of each classification accuracy metric are calculated and used for model evaluation.

Training a network involves random initialization, random data order, etc



Discussion Question 6

What is table two meant to show? How does it relate to concepts from last week's paper?

TFBS learns useful features

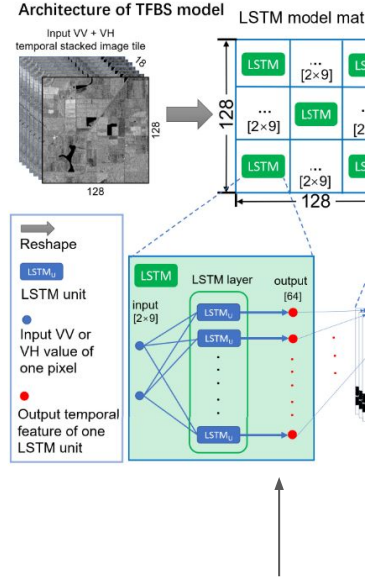


TABLE II
SEPARABILITY INDICATORS OF RICE IN RAW TIME-SERIES SAR IMAGES AND INTERMEDIATE TEMPORAL FEATURES MINED BY TFBS MODEL

	ARMSMOTN			Northern LA			Mean	Std.
	2017	2018	2019	2017	2018	2019		
J-M values of raw time-series images	1.34	1.36	1.22	1.43	1.39	1.36	1.350	0.065
J-M values of intermediate temporal features	2.00	2.00	2.00	2.00	2.00	2.00	2.00	0
TD of raw time-series images	1.46	1.47	1.37	1.57	1.54	1.5	1.485	0.064
TD of intermediate temporal features	2.00	2.00	2.00	2.00	2.00	2.00	2.00	0

J-M represents Jeffries-Matusita and TD represents Transformed Divergence indicator. ARMSMOTN represents Arkansas (AR), Mississippi (MS), southern Missouri (MO) and western Tennessee (TN). LA represents Louisiana.

Comparing how the output of the LSTM layer represents rice vs non-rice. I.e., looking at the representations that were learned.

Discussion Question 7

The authors note that the multi-class models confuse cotton for soybeans. Which model makes this mistake the most? What is another somewhat common mistake made by the models?

Confusion matrices

Soybeans are
also commonly
classified as
others

LSTM
makes
this error
the most



Fig. 18. Confusion matrixes of UNET, LSTM, TFBS, and ConvLSTM models. The models are trained by the augmented ARMSMOTN 2019 dataset and tested by the ARMSMOTN 2018 dataset.

Discussion Question 8

Share what questions you wrote in your PMIRO+Q and decide as a group what you'd like to ask.

Update your PMIRO+Q

Submit a second file to the Brightspace assignment (don't overwrite the original):

It should:

Update your PMIRO as needed

Answer your own Q

You can be talking with your group during this!

15 min break

Lecture

Career Day, Project Info, Exam Review

Alex Steffen, Climate Writer - *The Snap Forward*

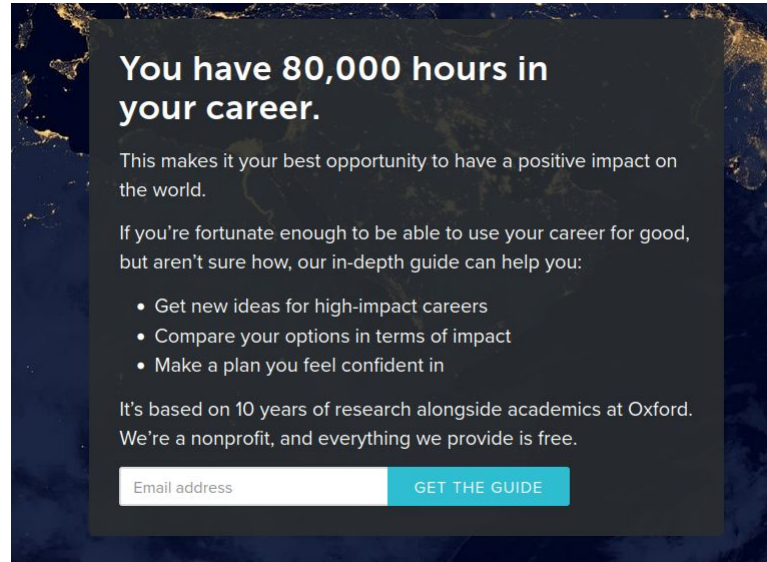
“We don’t get to choose whether the context of all our work is an unprecedented, all-encompassing planetary crisis. It simply is. There is nowhere to stand outside of it. We can pretend that’s not true — insist that our lives or work or special concerns will remain untouched by ecological catastrophe and societal upheaval — but in the long run, we’re just fooling ourselves.”



Climate career pathways

- Work directly on climate change
- Work directly on something else but bring awareness and action on climate to your job
- Regardless of your job, engage in climate action and activism

Your career is your biggest chance to make an impact



You have 80,000 hours in your career.

This makes it your best opportunity to have a positive impact on the world.

If you're fortunate enough to be able to use your career for good, but aren't sure how, our in-depth guide can help you:

- Get new ideas for high-impact careers
- Compare your options in terms of impact
- Make a plan you feel confident in

It's based on 10 years of research alongside academics at Oxford. We're a nonprofit, and everything we provide is free.

Email address

GET THE GUIDE

<https://80000hours.org/>

Working on climate

WORK ON CLIMATE Programs Resources Blog About Us Donate

Join us

We help you find a way to work on climate

We are an action-oriented Slack community for people serious about climate work. Find climate jobs. Build climate companies. Find your people.



Join us on Slack

How to use the community



Join the community

Share your journey, find collaborators, and celebrate each other's wins.



Explore our programs

Find the right community offering for where you are on your path.



Meet climate experts

Drop in to meet our friendly climate experts during regular office hours.



Find a job in climate

Find a climate job via our #jobs, #job-alerts and #gigs channels.

Work On Climate

Threads

Direct messages

Mentions & reactions

Drafts & sent

Saved items

Stack Connect

More

Channels

announcements

community-feedback

community-organisers

events-external

events-official

general

gigs

i-got-a-job

jobs

job-alerts

jobs-discussion

learn-psychology

learn-the-space

meet-nyc

need-help

project-work-deck

jobs

Check guidelines before posting Join #jobs- subchannels like #jobs-software-engineering #jobs-remote #jobs-software-engineering #jobs-regen

Today

Vlad Mikhaylov 8:21 AM

Stem is hiring a **Technical Product Manager** for the **AI Optimization** team! The role is focused around working with cross functional stakeholders and SMEs to ensure Stem continues to deliver industry-leading optimization capabilities in behind-the-meter and front-of-the-meter energy storage operations and simulations. The right candidate will own and extend optimization driven services and applications at Stem.

- Location: Remote / San Francisco
- Time commitment: Full time
- Compensation: Not known
- Connection to company: Currently report to hiring manager

More details found here: <https://www.linkedin.com/jobs/view/technical-product-manager-ai-optimization-applications-at-stem-inc-3520450371/>

If you are interested, feel free to dm me directly with resume or reach out with any questions!

5 replies Last reply today at 12:08 PM

Laura Rosenshine 10:44 AM

NEW ROLE ALERT TO HELP THE

WATS helps businesses streamline their waste operations, report on carbon impacts, and comply with shifting regulations. We are already making an impact at the intersection of sustainability and commercial waste management, and we are hiring our third engineer. This new addition to our team will help us ship features directly to users and join the foundational early days of our technology organization. About the role:

- Builder role who will be able to solve a wide range of technical challenges directly tied to the user and join a team with low technical debt.
- Top team including two co-founders, Meredith Danberg-Ficarelli & Laura Rosenshine, who have combined over two decades of experience in the commercial waste industry
- Full-Stack opportunity with preferred experience for Javascript & NodeJS (targeting at least four years of experience)
- Open to remote work in USA or Canada, NYC preferred
- Solving a critical mission for our environment and society

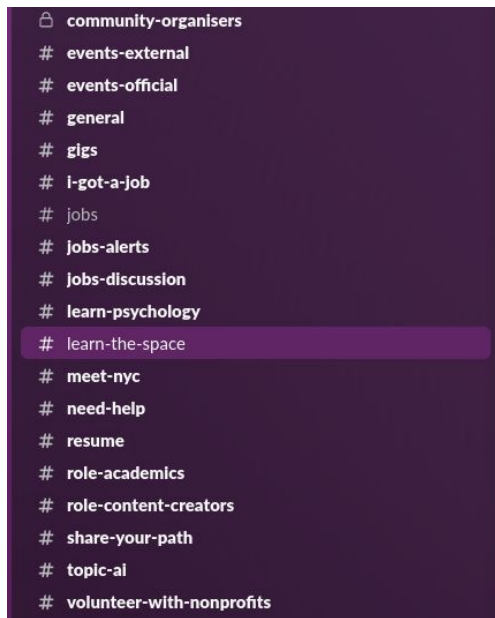
Please check out the [JD](#) for more information here. Send your resume to hello@getwats.com (edited)

Climatebase.org
Full Stack Developer | WATS
WATS is a climate tech company working to decarbonize commercial real estate with

Central Hub: <https://workonclimate.org/>

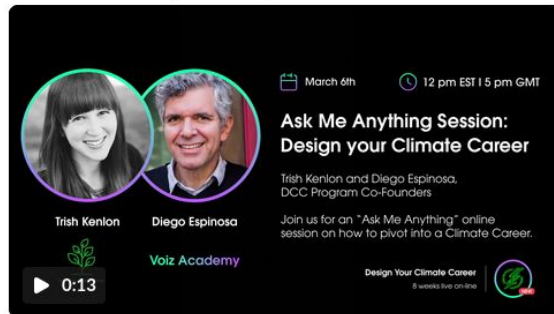
Working on climate

Communities help with resumes, interviews, skill learning etc.



#ClimateCareers #Sustainability #CareerDevelopment

Climate Careers Events by Voiz Academy.mov ▾



Mike Heavers 🗨️ 7:09 PM

👉 - anyone have any recommendations for good training courses for sustainability education in the tech space? (e.g. green software principles)



3 replies Last reply 2 days ago

Yesterday ▾

Working on climate

You can also look for volunteer or internship opportunities to skill up

- # announcements 1
- # community-feedback
- # community-organisers
- # events-external
- # events-official
- # general
- # gigs
- # i-got-a-job
- # jobs
- # jobs-alerts
- # jobs-discussion
- # learn-psychology
- # learn-the-space
- # meet-nyc
- # need-help
- # project-work-deck
- # resume
- # role-academics
- # role-content-creators
- # share-your-path
- # topic-ai
- # volunteering
- # introductions
- + Add channels



Anna K 10:49 AM

Has anyone here volunteered for Climate Neutral? I'd love to hear your thoughts on it!



3 replies Last reply 1 month ago



Geoff Skigen 1:58 PM

Calling all ocean activists. COARE (Center for Oceanic Awareness Research and Education), a global leader in conservation policy is looking for interns and volunteers.

I've been a volunteer for 1 year+ now and have loved every minute. I can say this org may be tiny, but it is mighty. They've achieved more than most marine conservation orgs triple their size.

COARE has written and passed substantial anti-shark finning policy at the United Nations and are also at the forefront of plastic pollution policy.

We're looking for Ocean Policy Interns, Ocean Program Interns, and Social Media Intern(s).

Click here for a full description: <https://www.coare.org/jobs/intern/>

Questions? Feel free to ping me on Slack or here: geoff@skigencreative.com (edited)



Wednesday, March 8th



Michael Hawk 4:54 PM

Hi Folks! I recently left Google to start a next-generation conservation organization (Jumpstart Nature) focused on biodiversity and climate. We're using technology and a multi-disciplinary approach to empower everyone to make a difference for the environment. In particular, we're looking at ways to leverage "new media" (apps, podcasts, games, etc) and behavioral science to get people off the sidelines. We're doing things that the large NGOs are ignoring or unable to do, and we need your help to keep pushing the boundaries of conservation.

I'm looking for volunteers that can help with podcast production (I can train you), campaign coordination across platforms, and marketing help in general.

We're in the early stage (filing for 501c3), so I'm also looking for a couple more board members - especially those with 501c3 experience and mobile app development experience.

We have a big vision and some great volunteers already. I'm happy to tell you more! Thanks!

11 3 6 3 2

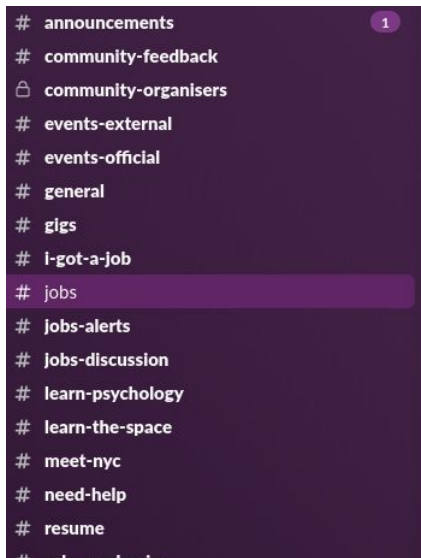


8 replies Last reply 13 days ago



Working on climate

Also job offers



Sabyasachi Kar

11:25 AM

I have sent you a direct message. Please respond.



Andrea Dennis

11:26 AM

Hi Community! The science and technology team of [Earthshot Labs](#) is hiring a [Senior Software Engineer](#). View the role description and apply here: <https://bit.ly/3SrjWu>

We are looking for someone to take ownership of the front end of LandOS, our web mapping and carbon development project information system. Key skills to be successful in the role include React, Python, MapBox, and intuitions about geospatial data. Having solid back-end skills is a plus. Earthshot provides tech-enabled carbon development support and cutting-edge scientific predictive analytics to enhance every stage of a carbon project. We work with global clients by leveraging technology to bring science-backed rigor to carbon markets to accelerate the development and financing of nature-based solutions. Our vision at Earthshot is to scale reforestation and conservation globally to a level that meets the ecological and climate crises challenge. The role is 100% remote.

Thanks in advance for sharing this opportunity with your networks. If you have any questions, please connect with me directly at andrea@earthshot.eco. [Apply here](#)



2 replies

Last reply 13 hours ago

Working on climate

Job boards:

<https://www.climatecareers.com/#jobboards>

<https://climatebase.org/>

<https://terra.do/climate-jobs/job-board/>

<https://www.climatejobsl.com>

<https://www.climatepeople.com/>

<https://climateaction.tech/> (slack)

Freelance: <https://www.leafr.work/>

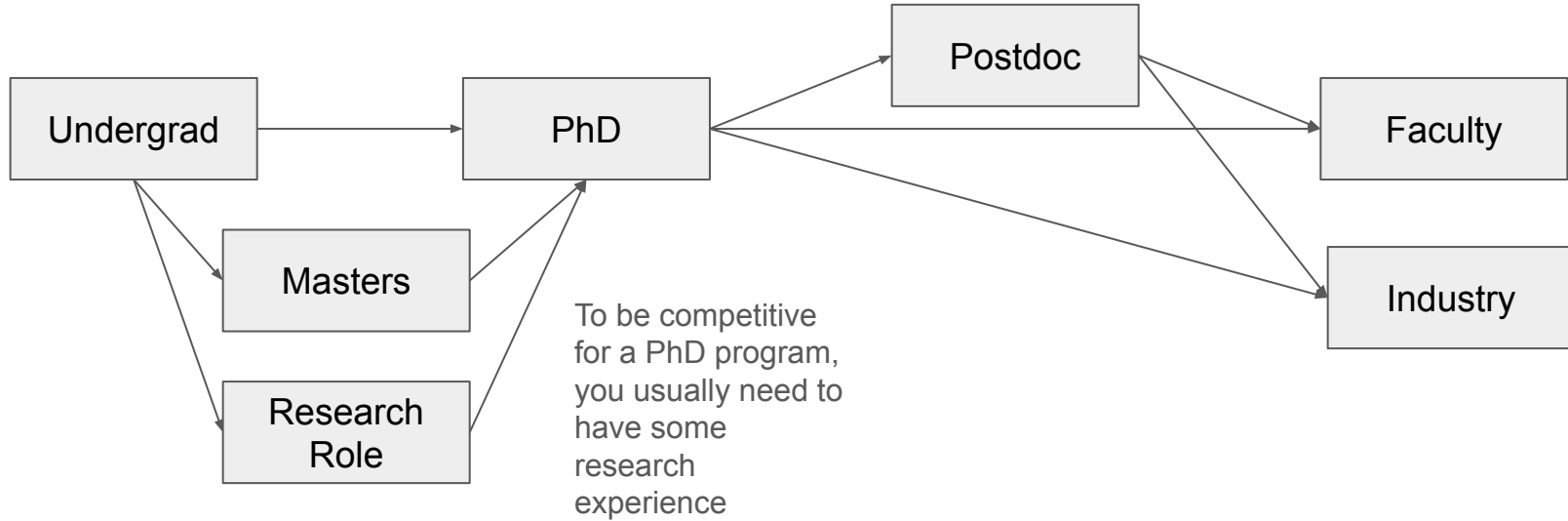
and more!

The screenshot displays the 'Climate Jobs List' website. At the top, it says '41 Climate jobs in New York City' with a US flag icon. Below this, a search bar is visible with the text 'Job title or keyword' and a location filter set to 'NEW YORK CITY'. The main content area lists several job openings:

- Senior Workforce Administrator** at BlocPower (7 days ago). Location: New York City, United States.
- Senior Storage Engineer** at Geli (8 days ago). Location: New York City, United States.
- Subcontracts Manager** at Geli (9 days ago). Location: New York City, United States.
- Senior Solar Estimator** at Geli (9 days ago). Location: New York City, United States.
- Quality Assurance Analyst** at Via Transportation.

On the right side, there is a 'Discover Climate Jobs' section with a search bar and filters. It shows job listings for 'Data Analyst' at Hayden AI, 'Senior Wildfire Data Scientist' at Overstory, and 'Sr Data Scientist' at NextEra Energy. At the bottom, there is a 'CLIMATE FELLOWSHIP' section with a link to 'Climate Change: Learning for Action' and an 'Apply now' button. Below this, there are two job listings: 'Team Lead (Manager) - Focused on climate analytics' at Marsh & McLennan Companies and 'Climate Data Scientist - Emissions Research' at Msci.

Academic Path



Learning more and networking

Climate Change AI summer school - https://www.climatechange.ai/events/summer_school
https://www.youtube.com/playlist?list=PLpPW7qLmXhdTnd9XSu606n2Qj93_-0O01

Terra.do School - <https://terra.do/>

One Point Five Academy - <https://www.opf.degree/opf-academy>

Airminers Boot-up - <https://airminers.org/learn>

Climatematch Academy - <https://academy.climatematch.io/>

Starting a company

My Climate Journey community and podcast: <https://www.mcjcollective.com/>

Resources for all stages: <https://climatefounder.org/>

Funding:

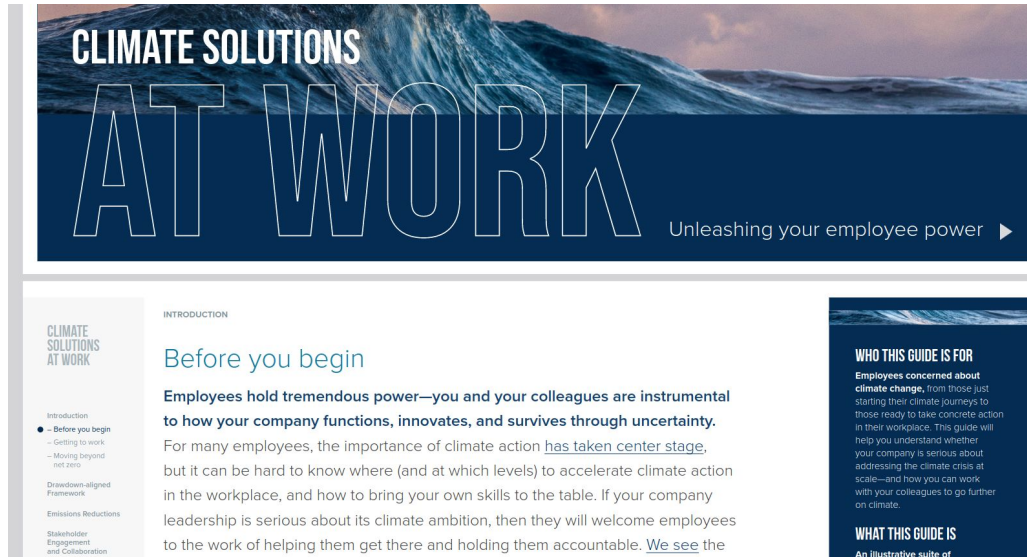
<https://www.climate.vc/>

<https://climatetechvc.org/>

<https://evergreeninno.org/>

Urban Future Lab @ NYU: <https://www.ufl.nyc/>

“Every job is a climate job”



<https://drawdown.org/publications/climate-solutions-at-work>

“Every job is a climate job”

	STATUS QUO		DRAWDOWN-ALIGNED
Emissions Reductions	Promises distant “net zero by 2050” commitment with reliance on offsets and no interim targets.	→	Moves on an accelerated timeline with interim targets and reduced reliance on offsets.
Stakeholder Engagement and Collaboration	Internal climate work is limited to sustainability teams and external engagement is primarily focused on investors.	→	Employees, communities, board members, and more are included.
Products, Partnerships, and Procurement	Products, partnerships, and procurement (the three Ps) are misaligned with climate commitments.	→	The three Ps are aligned with a company's sustainability strategy.
Investments and Financing	Corporate investments and employee retirement plans are misaligned with climate goals.	→	Business is fully divested from fossil fuels and invested in climate solutions.
Climate Disclosures	A lack of transparency on emissions and climate-related risks is the norm.	→	Public emissions and climate risk disclosures occur on a regular basis.
Climate Policy Advocacy	Corporate and trade associations are known to lobby against climate policy.	→	Lobbying and contributions support bold climate policy, including alignment from trade associations.
Business Model Transformation	Sustainability is an under-resourced add-on to the core business of the company.	→	Business models always shift center on scaling climate solutions.
Long-term Thinking	Business is focused on growth and quarterly returns.	→	Uses business influence to promote justice and shift economic paradigms to fit within planetary boundaries.

Where we are and where we need to go

Private-sector climate targets need to meet the global climate crisis at scale. Companies can become “drawdown-aligned” by meeting all of the requirements outlined in this guide.

“Every job is a climate job”

Work
forClimate

News

Resources ▼

Courses

About

Amplify your climate impact

WorkforClimate helps you **10x your impact** by guiding you through the steps required to take climate action at work

Find out more »

• CLIMATE CHANGEMAKERS

Case study: How one employee got a climate-friendly option added to her company's 401(k)

When Camille Smith realised that her company's default 401(k) portfolio (essentially, the American version of a superannuation fund) was lacking in environmentally conscious fund options, she decided to do something about it. Here's how her persistence paid off in making climate-friendly investing available to everyone at her company.

• GETTING STARTED

4 pressing climate questions to ask your CEO right now

Ask questions. Get your boss to take climate action seriously. Simple.

<https://www.workforclimate.org/>

“Every job is a climate job”

Neuron
NeuroView

Profession-specific
resources are becoming
more common

How Can Neuroscientists Respond to the Climate Emergency?

Adam R. Aron,^{1,*} Richard B. Ivry,² Kate J. Jeffery,³ Russell A. Poldrack,⁴ Robert Schmidt,⁵ Christopher Summerfield,^{6,*}
and Anne E. Urai⁷

¹Department of Psychology and Neuroscience Graduate Program, University of California San Diego, San Diego, USA

²Department of Psychology, University of California, Berkeley, USA

³Division of Psychology and Language Sciences, University College London, UK

⁴Department of Psychology, Stanford University, Stanford, CA, USA

⁵Department of Psychology, University of Sheffield, Sheffield, UK

⁶Department of Experimental Psychology, University of Oxford, Oxford, UK

⁷Cold Spring Harbor Laboratory, Cold Spring Harbor, NY, USA

*Correspondence: adamaron@ucsd.edu (A.R.A.), christopher.summerfield@psy.ox.ac.uk (C.S.)

<https://doi.org/10.1016/j.neuron.2020.02.019>

The world faces a climate emergency. Here, we consider the actions that can be taken by neuroscientists to tackle climate change. We encourage neuroscientists to put emissions reductions at the center of their everyday professional activities.

“Every job is a climate job”



Rapid, Far-reaching, Unprecedented Change.

The climate crisis is happening all around us. As tech workers, we can use our skills to take and accelerate climate action.

At ClimateAction.tech, we meet, discuss, learn and take climate action together.
We would love for you to join us on Slack.

[JOIN US ON SLACK](#)

Our Focus Areas

The internet is the world's largest machine. If we continue business-as-usual, the IT sector will be responsible for 14% of the world's carbon emissions by 2040 [\[HBR, 2020\]](#). From our community conversations, these 4 subjects have emerged as levers for changing our industry:



Business Culture & Behavior Change

We want businesses to prioritize climate issues and embed sustainability requirements into the day-to-day work of all employees.



Green Software Engineering

Software engineers can make decisions which reduce the carbon pollution of their applications.



Sustainable Product Design

We can change the product design process to reduce upstream and downstream emissions.



Low-Carbon Infrastructure

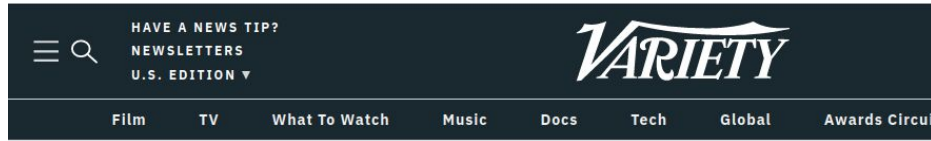
While we transition to renewable energy, we can align compute load with low-carbon energy.

Profession-specific resources are becoming more common

<https://climateaction.tech/>

“Every job is a climate job”

Profession-specific resources are becoming more common



HOME > MUSIC > NEWS

Jul 12, 2022 7:55am PT

Here's How the Music Industry Can Help Fight Climate Change (Guest Column)

By Jem Aswad



Tech Marketing Media Executive Transactions All Topics

Daily Editions | Newsletters |

Sports industry needs to make climate change a priority

BY AYELET MAVOR
Monday, January 10, 2022

Climate action outside of work

Stay informed! Newsletters/media sites:

- <https://www.carbonbrief.org>
- <https://grist.org/>
- <https://www.volts.wtf/>
- <https://heated.world/>

Climate action outside of work

Non-profits working on climate issues

- Clean Air Task Force
- Earthjustice
- Conservation International
- CarbonFund
- Environmental Defense Fund
- many more!

Climate action outside of work

Political organizing

- Citizens' Climate Lobby
- League of Conservation Voters
- Extinction Rebellion
- People's Climate Movement

REPORT | MAY 26, 2021

Gen Z, Millennials Stand Out for Climate Change Activism, Social Media Engagement With Issue



ANNALS OF A WARMING PLANET

THE ANSWER TO CLIMATE CHANGE IS ORGANIZING

Dealing with global warming is always going to be about the balance of power.



By Bill McKibben
September 1, 2021

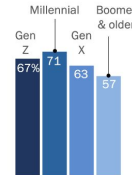
Gen Z, Millennials more active than older generations addressing climate change on- and offline

% of U.S. adults who say ...

Climate should be top priority to ensure sustainable planet for future generations

Addressing climate change is my top personal concern

Have personally taken action to help address climate change within the last year

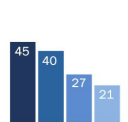
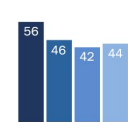
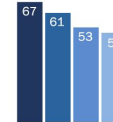


In the past few weeks ...

Talked about need for action on climate at least 1-2 times

Seen content on social media about need for climate action

Engaged on social media with content on need for climate action



Note: Respondents who gave other responses or did not give an answer are not shown. Seen content on social media and engaged with climate content based on social media users.

Source: Survey conducted April 20-29, 2021.

"Gen Z, Millennials Stand Out for Climate Change Activism, Social Media Engagement With Issue"

PEW RESEARCH CENTER

Climate action outside of work

WHAT WE DO:

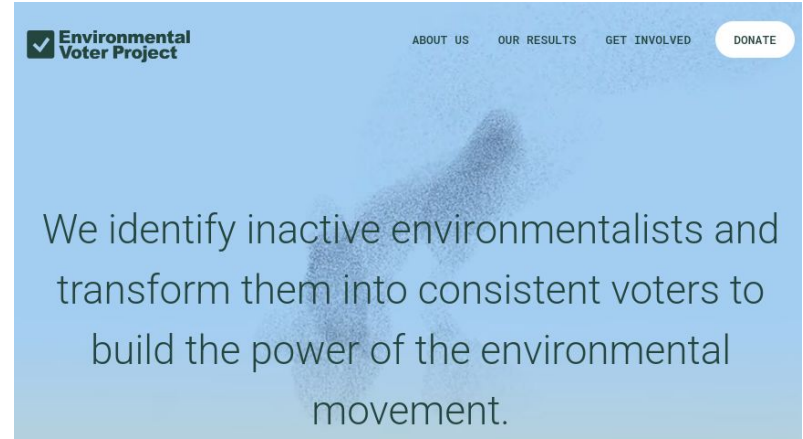
#FridaysForFuture is a youth-led and -organised movement that began in August 2018, after 15-year-old Greta Thunberg and other young activists sat in front of the Swedish parliament every schoolday for three weeks, to protest against the lack of action on the climate crisis. She posted what she was doing on Instagram and Twitter and it soon went viral.

7,500
Cities

+14,000,000
People

ALL
Continents

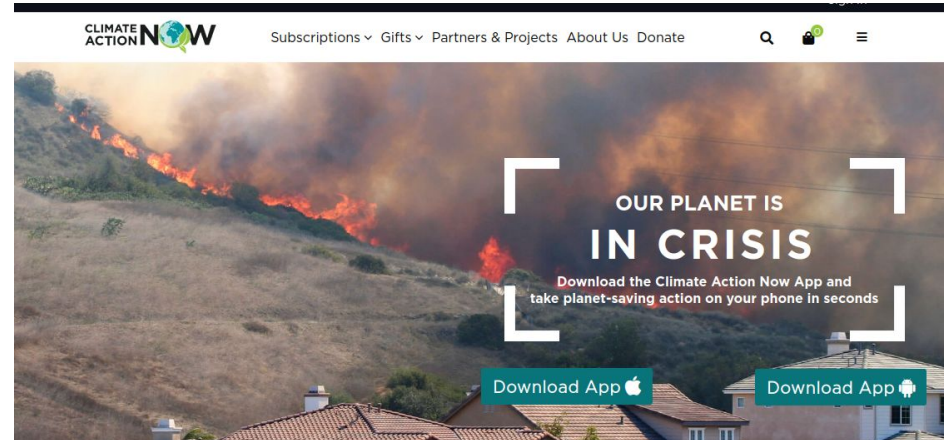
GET TO KNOW US



Environmental Voter Project

ABOUT US OUR RESULTS GET INVOLVED DONATE

We identify inactive environmentalists and transform them into consistent voters to build the power of the environmental movement.





CLIMATE ACTION NOW

Subscriptions ▾ Gifts ▾ Partners & Projects About Us Donate

OUR PLANET IS IN CRISIS

Download the Climate Action Now App and take planet-saving action on your phone in seconds

Download App  Download App 

Projects Overview

The class project is your chance to go deeper into a question, dataset, and/or method you are interested in.

You will be evaluated on your ability to pose a good machine learning question in the domain of climate change, the selection and execution of relevant methods, your ability to work on a team, and your presentation skills both written and oral.

Project teams

Everyone must work in a team (no individual projects)

Teams should be 5 people

A single grade will be given to the team.

Projects

Projects need to go beyond what you have done in homework assignments.

Possible approaches:

- replicate/extend an existing paper
- contribute to an established competition/benchmark
- Identify an underexplored problem where ML could help and try to solve it

Projects

Rough guidelines for creating a **substantial** project:

- Compare multiple methods and/or hyperparameters
- Use at least one method that isn't in scikit-learn (Rijul will be going through PyTorch code in labs)
- Explore feature importance methods
- Create your own dataset from multiple sources
- Use multiple evaluation methods
- Include advanced visualizations and/or a dashboard (but it better be really good)
- etc

Possible data sources

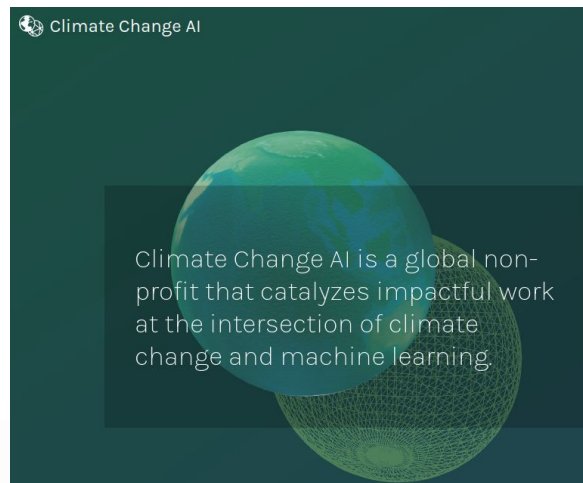
Here are locations to look for relevant data. Not all datasets from these sources will be climate change-related.

Note: these are real datasets. They may have missing data, poor documentation, or other challenges. You will probably have to teach yourselves some new skills to get what you want from them. These are all things data scientists have to face! Look into a dataset before committing to using it.

Starting Points

Climate Change AI

<https://www.climatechange.ai/papers>



Climate Change AI Workshop Papers

On this page, we show accepted works from all our [workshops](#) on "Tackling Climate Change with Machine Learning."

Venue	Text Search	Subject Areas	Award?
All Venues	<input type="text" value="Enter search terms..."/>	<input type="text" value="Select some options..."/>	<input type="checkbox"/>

Showing 1 to 728 of 728 entries

Venue	Title	Subject Areas
NeurIPS 2023	Machine learning for gap-filling in greenhouse gas emissions databases (Papers Track) ► Abstract and authors: (click to expand)	Public Policy
NeurIPS 2023	EarthPT: a foundation model for Earth Observation (Papers Track) ► Abstract and authors: (click to expand)	Earth Observation & Monitoring
NeurIPS 2023	Towards Understanding Climate Change Perceptions: A Social Media Dataset (Papers Track) ► Abstract and authors: (click to expand)	Behavioral and Social Science

Starting Points

Climate Change AI

https://www.climatechange.ai/subject_areas

Subject Areas

Here, we provide a window into our content by subject area. Click on an area to see related papers, blog posts, webinars, and tutorials.

Applications

- [Agriculture & Food](#)
- [Behavioral and Social Science](#)
- [Buildings](#)
- [Carbon Capture & Sequestration](#)
- [Chemistry & Materials](#)
- [Cities & Urban Planning](#)
- [Climate Finance & Economics](#)
- [Climate Justice](#)
- [Climate Policy](#)
- [Climate Science & Modeling](#)
- [Disaster Management and Relief](#)
- [Earth Observation & Monitoring](#)
- [Ecosystems & Biodiversity](#)

AI Methods

- [Active Learning](#)
- [Causal & Bayesian Methods](#)
- [Computer Vision & Remote Sensing](#)
- [Control Systems](#)
- [Data Mining](#)
- [Forecasting](#)
- [Generative Modeling](#)
- [Hybrid Physical Models](#)
- [Interpretable ML](#)
- [Meta- and Transfer Learning](#)
- [Natural Language Processing](#)
- [Optimization](#)
- [Recommender Systems](#)

Starting Points

Climate Change AI

<https://www.climatechange.ai/tutorials>

Tutorials

Text Search

Topic

All Topics

Difficulty

All Levels

Subject Areas

Select some options...



Agile Modeling for Bioacoustic Monitoring



Jenny Hamer, Rob Laber, and Tom Denton, NeurIPS 2023

Bioacoustic monitoring promises to help unlock the ability to monitor biodiversity, ecosystem health, and endangered species cost effectively. This tutorial presents an "agile modeling" approach that enables users to build custom classifier systems efficiently for species of interest using transfer learning, audio search, and human-in-the-loop active learning.

Ecosystems and Biodiversity Intermediate Python Bioacoustics Audio/Acoustics

Search Human-in-the-Loop Ecosystems & Biodiversity Active Learning



Aquaculture Mapping: Detecting and Classifying Aquaculture Ponds using Deep Learning



Joshua Cortez and John Christian Nacpil, NeurIPS 2023

Managing aquaculture ponds is vital for environmental monitoring and conservation. This tutorial presents how to leverage satellite imagery and semantic segmentation models to detect and map aquaculture ponds based

Starting Points

Climate Change AI

https://wiki.climatechange.ai/wiki/Welcome_to_the_Climate_Change_AI_Wiki

Welcome to the Climate Change AI Wiki

[Main Page](#) [Discussion](#)

[Read](#) [Edit](#) [Edit source](#) [View history](#) [Tools](#) ▼

This is the approved revision of this page, as well as being the most recent.

The aim of this wiki is to help foster impactful research to tackle climate change, by identifying areas for a useful implementation of machine learning (ML).

The scope of machine learning solutions to address climate change goes far beyond the intersection we address here. Tackling climate change requires cooperation between diverse stakeholders, domain scientists, and action in many forms. Whether you are a machine learning researcher looking to apply your skills to combat climate change, or an early career researcher aiming to have a meaningful impact in your career, a practitioner in one of the domain science areas looking to apply ML to your problem, or for any other reason you are interested in the intersection of climate change and ML, we hope these pages can help inform and facilitate your research!

We welcome your contributions and feedback! This wiki is maintained and moderated by members of [CCAI](#).

See [guide on contributing to the CCAI Wiki](#). Feel free to start suggesting changes to any of the following pages!

If you would like to discuss your ideas for additional pages or gain moderator privileges, feel free to reach out to CCAI at wiki@climatechange.ai.

Quick start [\[edit | edit source \]](#)

- [General Resources](#) page
- [Tackling Climate Change with Machine Learning](#) review paper or explore its [interactive summary](#)!
- Explore the [Climate Change AI Workshop papers](#)

Topics by Application Area [\[edit | edit source \]](#)

The pages below provide overviews and resources on topics at the intersection of climate change and machine learning. *Mitigation* refers to reducing emissions in order to lessen the extent of climate change, while *adaptation* refers to preparing for the effects of climate change. We also provide overviews of various *tools for action* -- such as policy, economics, education, and finance -- that can help enable mitigation and adaptation strategies.

Mitigation [\[edit | edit source \]](#)

- [Electricity systems](#)
- [Transportation](#)
- [Buildings and cities](#)

Places to find data

Kaggle - can look at competitions and data sets (but pay attention to quality!)

www.kaggle.com

Twitter Climate Change Sentiment Dataset

44k tweets pertaining to climate change



Data Card Code (8) Discussion (0)

About Dataset

The collection of this data was funded by a Canada Foundation for Innovation JELF Grant to Chris Bauch, University of Waterloo.

This dataset aggregates tweets pertaining to climate change collected between Apr 27, 2015 and Feb 21, 2018. In total, 43943 tweets were annotated. Each tweet is labelled independently by 3 reviewers. This dataset only contains tweets that all 3 reviewers agreed on (the rest were discarded).

Each tweet is labelled as one of the following classes:

- 2 (News): the tweet links to factual news about climate change
- 1 (Pro): the tweet supports the belief of man-made climate change
- 0 (Neutral): the tweet neither supports nor refutes the belief of man-made climate change
- -1 (Anti): the tweet does not believe in man-made climate change

The distribution of the data:

Waste Classification data

This dataset contains 22500 images of organic and recyclable objects

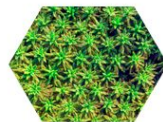
Data Card Code (71) Discussion (0)

<https://www.kaggle.com/datasets/techsash/waste-classification-data>

Places to find data

Zindi (can use closed or open competitions)

<https://zindi.africa/competitions>



Digital Africa Plantation Counting Challenge

Can you create a semi-supervised algorithm to count trees in plantations in Côte d'Ivoire?

Advanced Prediction Computer Vision Agriculture

\$10 000 USD

~1 month to go

76 active participants
268 enrolled

Helping Côte d'Ivoire



Africa Biomass Challenge

Can you predict biomass in cocoa plantations in Côte d'Ivoire?

Advanced Prediction Agriculture

\$10 000 USD

3 months to go

106 active participants
666 enrolled

Helping Côte d'Ivoire



Intron AfriSpeech-200 Automatic Speech Recognition Challenge

Can you create an automatic speech recognition (ASR) model for African accents, for use by doctors?

Advanced Automatic Speech Recognition Media Health

\$5 000 USD

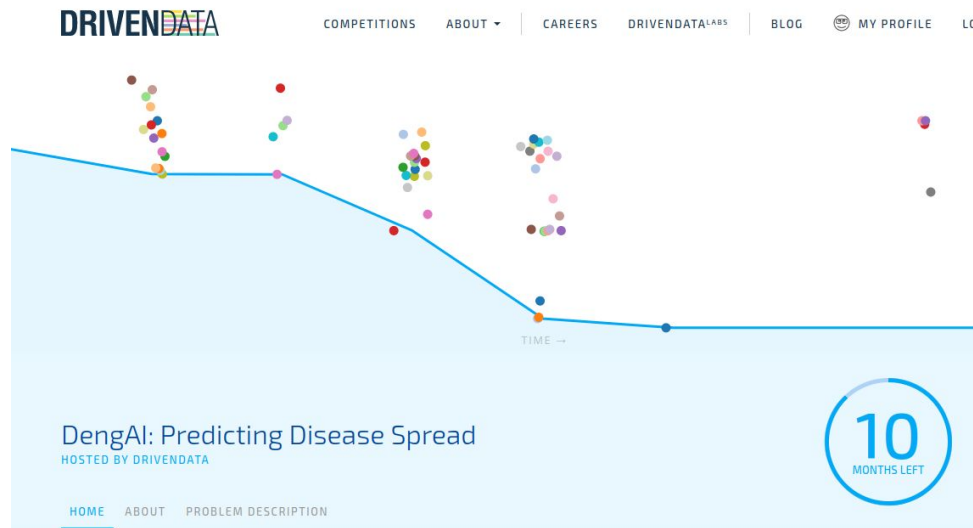
3 months to go

5 active participants
148 enrolled

Places to find data

Driven Data competitions

<https://www.drivendata.org/competitions/>



Challenge Summary

Can you predict local epidemics of dengue fever?

Dengue fever is a mosquito-borne disease that occurs in tropical and sub-tropical parts of the world. In mild cases, symptoms are similar to the flu: fever, rash, and muscle and joint pain. In severe cases, dengue fever can cause severe bleeding, low blood pressure, and even death.



LEADERBOARD

DATA DOWNLOAD

SUBMISSIONS

Possible data sources

<https://opendata.cityofnewyork.us/>

Has an “environmental” section.
Contains data on trees, air quality,
energy use, sea level, etc.

The screenshot displays the NYC OpenData website interface. At the top, the 'NYC OpenData' logo is on the left, and navigation links for 'Home', 'Data', 'About', 'Learn', 'Alerts', 'Contact Us', and 'Blog' are on the right. A search bar contains the text 'climate'. Below the search bar, a sidebar on the left lists 'Categories' (Business, City Government, Education, Environment, Health) and 'View Types' (Data Lens pages, Datasets, External Datasets, Files and Documents). The main content area shows '60 Results' and a 'Sort by' dropdown set to 'Most Accessed'. Three results are visible:

- Sea Level Rise Maps (2050s 500-year Floodplain)** (Environment): This is the 500-Year Floodplain for the 2050s based on FEMA's Preliminary Work Map data and the New York Panel on Climate Change's 90th Percentile Projects for Sea-Level Rise (31 inches). Please see the Disclaimer PDF for more. Updated September 16, 2021. Views 33,366. Tags: sea level rise maps (2050s 500-year floodplain), sea, flood, ocean, floodplain.
- Sea Level Rise Maps (2020s 100-year Floodplain)** (Environment): This is the 100-Year Floodplain for the 2020s based on FEMA's Preliminary Work Map data and the New York Panel on Climate Change's 90th Percentile Projects for Sea-Level Rise (11 inches). Please see the Disclaimer PDF for more. Updated September 16, 2021. Views 21,768. Tags: sea, flood, ocean, oltps, sea level rise maps (2020s 100-year floodplain).
- Natural Gas Consumption by ZIP Code - 2010** (Environment): 2010 Natural Gas consumption in therms and GJ, by ZIP code, building type, and utility company. Updated May 9, 2022. Views 1,000. Tags: gas, planning, power, energy, utilities, and 1 more.

Possible data sources

Energy information administration

<https://www.eia.gov/totalenergy/data/annual/index.php>

[SEE ALL REPORTS](#)

Annual Energy Review

Superseded -- see MER for key annual tables

Annual Energy
Year

EIA has expanded the *Monthly Energy Review* (MER) to include annual data as far back as 1949 for those data tables that are found in both the *Annual Energy Review* (AER) and the [MER](#). In the list of tables below, grayed-out table numbers now go to MER tables that contain data series for 1949 forward. New [INTERACTIVE tables and graphs](#) have also been added.

DATA CATEGORIES

[EXPAND ALL](#)

- [+ Energy overview](#)
- [+ Energy consumption by sector](#)
- [+ Financial indicators](#)
- [+ Energy resources](#)
- [+ Petroleum and other liquids](#)
- [+ Natural gas](#)
- [+ Coal](#)
- [+ Electricity](#)
- [+ Nuclear energy](#)
- [+ Renewable energy](#)
- [+ Environment](#)
- [+ Appendices \(heat content, conversion factors, and more\)](#)

Possible data sources

Emissions estimations from NEI

<https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei>

ClimateTRACE emissions data

<https://climatetrace.org/downloads>

Carbon dioxide data from remote sensing

https://disc.gsfc.nasa.gov/datasets/OCO2GriddedXC_O2_3/summary?keywords=oco-2

On road emissions data

https://daac.ornl.gov/CMS/guides/CMS_DARTE_V2.html

Air Emissions Inventories

[CONTACT US](#)

[Air Emissions Inventory Home](#)

[Data and Documentation](#)

[2020 NEI Data](#)

[2017 NEI Data](#)

[2014 NEI Data](#)

[2011 NEI Data](#)

[2008 NEI Data](#)

National Emissions Inventory (NEI)

The National Emissions Inventory (NEI) is a comprehensive and detailed estimate of air emissions of criteria pollutants, criteria precursors, and hazardous air pollutants from air emissions sources. The NEI is released every three years based primarily upon data provided by State, Local, and Tribal air agencies for sources in their jurisdictions and supplemented by data developed by the US EPA. The NEI is built using the [Emissions Inventory System \(EIS\)](#) first to collect the data from State, Local, and Tribal air agencies and then to blend that data with other data sources.

DOWNLOADS

Climate TRACE emissions data is free and publicly available for download below. Each download package includes annual country-level emissions by sector and by greenhouse gas from 2015-2021, the applicable inventory of facility-level emissions, and facility-level ownership data where available.

Possible data sources

Open Street Map for general land and road features

<https://www.openstreetmap.org>

https://wiki.openstreetmap.org/wiki/Environmental_OSM

Environmental OSM

English [español](#) [русский](#) [日本語](#)

Environmental OSM - Other languages

[Other languages](#) · [Translate](#)

Environmental OSM is a project to map out various systems that have an impact on the environment in hopes of helping to solve environmental problems.

Please use the [discussion page](#) to suggest and discuss other data we might survey and other uses for the data.

Contents [hide]

- 1 Objectives
- 2 Tags
 - 2.1 Energy
 - 2.2 Environmental monitoring
 - 2.3 Waste/recycling
 - 2.4 Food
 - 2.5 Transport
 - 2.6 Natural habitats / land use
 - 2.7 Green space
- 3 Environmental features in development
- 4 Related initiatives
 - 4.1 OpenStreetMap
 - 4.2 Other
- 5 People interested
- 6 Contact

Possible data sources

Bureau of Transportation
Statistics

https://www.bts.gov/product/national-transportation-statistics?keys=miles&field_topic_target_id=All



[Amtrak Fuel Consumption and Travel](#)



[Amtrak Fuel Consumption and Travel \(Metric\)](#)



[Amtrak On-Time Performance Trends and Hours of Delay by Cause](#)



[Annual Roadway Congestion Index](#)



[Automobile Profile](#)



[Average Cost of Owning and Operating an Automobile](#)



[Average Fuel Efficiency of U.S. Light Duty Vehicles](#)



[Average Fuel Efficiency of U.S. Light Duty Vehicles \(metric\)](#)



[Average Length of Haul, Domestic Freight and Passenger Modes](#)



[Average Length of Haul, Domestic Freight and Passenger Modes \(metric\)](#)



[Average Passenger Revenue per Passenger-Mile](#)



[Bus Fuel Consumption and Travel \(metric\)](#)

Possible data sources

UN agriculture data (crop and livestock, yields, land area, etc)

<https://www.fao.org/faostat/en/#data>

Data on what crops are where:

https://www.nass.usda.gov/Research_and_Science/Cropland/sarsfaqs2.php#Section1_1.0

The screenshot shows the FAO FAOSTAT website. The header is blue with the FAO logo and text 'Food and Agriculture Organization of the United Nations'. A search bar is in the top right. Below the header, there's a navigation bar with tabs: 'Data', 'Selected Indicators', 'Compare Data', 'Definitions and Standards', and 'FAQ'. The 'Data' tab is active. Below this, there's a 'Data' section with a 'DOMAINS' tab selected. The 'DOMAINS' section lists various data categories in two columns, each with a right-pointing arrow and an icon. The categories are: Production, Food Security and Nutrition, Food Balances, Trade, Prices, Land, Inputs and Sustainability, Cost and Affordability of a Healthy Diet, Population and Employment, Investment, Macro-Economic Indicators, Food Value Chain, Climate Change, Forestry, SDG Indicators, World Census of Agriculture, and Discontinued archives and data series. Some categories have SDG indicator icons next to them.

FAO Food and Agriculture Organization of the United Nations

powered by Google

About FAO | In Action | Countries | Themes | Media | Publications | Statistics | Partnerships

العربية 中文 English Français Русский Español

FAOSTAT

Home Data Selected Indicators Compare Data Definitions and Standards FAQ Search an Indicator or Commodity

Data

DOMAINS DOMAINS TABLE

- Production
- Food Security and Nutrition SDG Indicators
- Food Balances
- Trade
- Prices
- Land, Inputs and Sustainability
- Cost and Affordability of a Healthy Diet
- Population and Employment
- Investment SDG Indicator
- Macro-Economic Indicators
- Food Value Chain
- Climate Change
- Forestry
- SDG Indicators
- World Census of Agriculture
- Discontinued archives and data series

Possible data sources

Global temperatures

<https://www.ncei.noaa.gov/products/land-based-station/noaa-global-temp>

[Home](#) / [Products](#) / [Land-Based Station](#) / NOAAGlobalTemp

NOAAGlobalTemp

The NOAA Merged Land Ocean Global Surface Temperature Analysis (NOAAGlobalTemp, formerly known as [MLOST](#)) combines long-term sea surface (water) temperature (SST) and land surface (air) temperature datasets to create a [complete, accurate depiction of global temperature trends](#). The dataset is used to support climate monitoring activities such as the Monthly Global Climate Assessment, and also provides input data for a number of climate models.

Possible data sources

Satellite datasets

<https://deepcube-h2020.eu/technology/earth-system-data-cube/>

<https://deepcube-h2020.eu/datasets/>

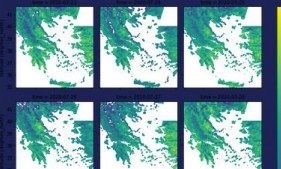
<https://github.com/satellite-image-deep-learning/datasets>

Data cube for drought forecasting in Africa

This is a dataset of minicubes suitable for Earth Surface Forecasting, created by the DeepCube research team of the Max Planck Institute for Biogeochemistry. The dataset is focused on Africa and the task is centered around drought impact forecasting.

To learn more about the Africa minicubes please visit <https://www.earthnet.tech/docs/ds-africa/>

Data cube for the wildfire research community



This dataset has been created by the DeepCube research team of the National Observatory of Athens and is meant to be used to develop models for next day fire hazard forecasting in Greece.

The dataset includes dynamic variables, such as previous day Leaf Area Index, evapotranspiration, Land Surface Temperature, meteorological data, fire variables and Fire Weather Index, resampled at daily temporal resolution and 1km spatial resolution. It also includes static variables, such as roads density, population density and topography layers.

Possible data sources

Extreme weather events

<https://github.com/andregraubner/ClimateNet>

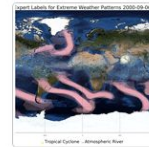
<https://gmd.copernicus.org/articles/14/107/2021/>

Model description paper | 

08 Jan 2021

ClimateNet: an expert-labeled open dataset and deep learning architecture for enabling high-precision analyses of extreme weather

Prabhat , Karthik Kashinath , Mayur Mudigonda , Sol Kim, Lukas Kapp-Schwoerer, Andre Graubner, Ege Karasimiloglu, Leo von Kleist, Thorsten Kurth, Annette Greiner, Ankur Mahesh, Kevin Yang, Colby Lewis, Jiayi Chen, Andrew Lou, Sathyavat Chandran, Ben Toms, Will Chapman, Katherine Dagon, Christine A. Shields, Travis O'Brien, Michael Wehner, and William Collins



Abstract

Identifying, detecting, and localizing extreme weather events is a crucial first step in understanding how they may vary under different climate change scenarios. Pattern recognition tasks such as classification, object detection, and segmentation (i.e., pixel-level classification) have remained challenging problems in the weather and climate sciences. While there exist many empirical heuristics for detecting extreme events, the disparities between the output of these different methods even for a single event are large and often difficult to reconcile. Given the success of deep learning (DL) in tackling similar problems in computer vision, we advocate a DL-based approach. DL, however, works best in the context of supervised learning – when labeled datasets are readily available. Reliable labeled training data for extreme weather and climate events is scarce.

We create “ClimateNet” – an open, community-sourced human-expert-labeled curated dataset that captures tropical cyclones (TCs) and atmospheric rivers (ARs) in high-resolution climate model output from a simulation of a recent historical period. We use the curated ClimateNet dataset to train a state-of-the-art DL model for pixel-level identification – i.e., segmentation – of TCs and ARs. We then apply the trained DL model to historical and climate change scenarios simulated by the Community Atmospheric Model (CAM5.1) and show that the DL model accurately segments the data into TCs, ARs, or “the background” at a pixel level. Further, we show how the segmentation results can be used to conduct spatially and temporally precise analytics by quantifying distributions of extreme precipitation conditioned on event types (TC or AR) at regional scales. The key contribution of this work is that it paves the way for DL-based automated, high-fidelity, and highly precise analytics of climate data using a curated expert-labeled dataset – ClimateNet.

Google Earth Engine

Hosts a variety of remote sensing and geospatial datasets

Has a Python API

Google Earth Engine

Starting November 13, 2024, all Earth Engine access will [require a Cloud project](#). We will b

A planetary-scale platform for Earth
science data & analysis

Powered by Google's cloud infrastructure

▶ Watch Video

More paper examples

<https://ai4good.org/fragile-earth-2022/>

<https://www.cambridge.org/core/journals/environmental-data-science>

<https://www.hadr.ai/accepted-papers>

https://openaccess.thecvf.com/CVPR2023_workshops/EarthVision

Want a certain type of data?

Check if there is a government or international agency about it (fingers crossed the data is still there)

Or google (particularly google scholar)

Or ask me

Possible methods

Supervised classification or regression (classic methods, simple artificial neural networks, advanced artificial neural networks)

Computer vision (simple feature extraction, convolutional neural networks)

Self- or Unsupervised methods for representation learning (pca, clustering, artificial neural networks)

Feature importance

Reinforcement learning

Project report

Abstract - a one paragraph summary of the full report

Background - what problem are you addressing, how does it relate to climate change, how has it been approached in the past, how are you approaching it and why

Methods - what data are using, how did you process it, what methods are using, how did you decide hyperparameters, how are you evaluating your model

Results - what did your methods show, what worked and what didn't work, includes pointers to figures

Discussion - what do your results mean, what would you do in the future if you were to continue working on this project, how do your results relate to other studies

References - bibliography of sources you used and cited

Author Contributions - state what work each member of the group did

~3 pages min for first five sections, plus extra pages for references and figures. Plus pre-run python notebook (should replicate your figures from data).

Project Presentations

~10 minutes. Summary of your project report. Should include all the same sections.

All team members must speak in the project presentation.

There will be additional time for questions from other students (required) and me

Advice

Think big (could even result in a publication). This is a growth opportunity.

Choose something meaningful and interesting to you.

Expect things to take a while and be frustrating, especially as you get started with new data or methods

Document what you are doing for yourself and for your final report

Manage your time! Work steadily, don't wait until the end

Research Quality

How to avoid machine learning pitfalls: a guide for academic researchers

Michael A. Lones*

Abstract

This document is a concise outline of some of the common mistakes that occur when using machine learning, and what can be done to avoid them. Whilst it should be accessible to anyone with a basic understanding of machine learning techniques, it was originally written for research students, and focuses on issues that are of particular concern within academic research, such as the need to do rigorous comparisons and reach valid conclusions. It covers five stages of the machine learning process: what to do before model building, how to reliably build models, how to robustly evaluate models, how to compare models fairly, and how to report results.

<https://arxiv.org/pdf/2108.02497.pdf>

Contents

1	Introduction	1
2	Before you start to build models	3
2.1	Do take the time to understand your data	3
2.2	Don't look at <i>all</i> your data	3
2.3	Do make sure you have enough data	3
2.4	Do talk to domain experts	4
2.5	Do survey the literature	4
2.6	Do think about how your model will be deployed	5
3	How to reliably build models	5
3.1	Don't allow test data to leak into the training process	5
3.2	Do try out a range of different models	6
3.3	Don't use inappropriate models	7
3.4	Do keep up with recent developments in deep learning	8
3.5	Don't assume deep learning will be the best approach	8
3.6	Do optimise your model's hyperparameters	9
3.7	Do be careful where you optimise hyperparameters and select features	9
3.8	Do avoid learning spurious correlations	11
4	How to robustly evaluate models	11
4.1	Do use an appropriate test set	11
4.2	Don't do data augmentation <i>before</i> splitting your data	12
4.3	Do use a validation set	12
4.4	Do evaluate a model multiple times	12
4.5	Do save some data to evaluate your final model instance	14
4.6	Don't use accuracy with imbalanced data sets	14
4.7	Don't ignore temporal dependencies in time series data	15
5	How to compare models fairly	16
5.1	Don't assume a bigger number means a better model	16
5.2	Do use statistical tests when comparing models	16
5.3	Do correct for multiple comparisons	17
5.4	Don't always believe results from community benchmarks	17
5.5	Do consider combinations of models	17
6	How to report your results	18
6.1	Do be transparent	18
6.2	Do report performance in multiple ways	19
6.3	Don't generalise beyond the data	19
6.4	Do be careful when reporting statistical significance	19
6.5	Do look at your models	20
7	Final thoughts	20

Writing evaluation

Your writing should be clear and concise, with minimal grammatical errors.

To write your background, find some example papers that may have tackled a similar problem so that you can situate your work relevant to past work (probably should do this before you start!).

For the methods, be clear and complete enough that someone could roughly replicate what you did just from reading your methods section.

Figures should be easy to understand, with clearly labeled axes and not too many different colors or line styles.

Presentation Evaluation

Slides should have clear and informative titles

Figures should be fully visible with labeled axes

Slides should not have too much written text; rather, you should have one or two main points on the slide with one or two major visuals. Elaborate on what is on the slides as you speak.

Speak loud enough for everyone to hear

Go at the right pace throughout (time yourself beforehand!)

Advice: imagine yourself in the audience listening to a project you know nothing about. How would you want the speaker to communicate to you?

Chat GPT

What are some academic papers that use machine learning to help with building energy efficiency?

Here are some academic papers that explore the use of machine learning for improving building energy efficiency:

1. "A Survey of Machine Learning Techniques for Building Energy Management"

- **Authors:** Hossain, M. S., & O'Brien, W.
- **Published in:** *Energy and Buildings* (2018)
- **Summary:** This paper provides a comprehensive review of how machine learning techniques, such as supervised learning, unsupervised learning, and reinforcement learning, can be applied to various aspects of building energy management. It discusses applications such as HVAC (Heating, Ventilation, and Air Conditioning) optimization, energy consumption prediction, and fault detection in buildings.

2. "Deep Learning for Building Energy Prediction: A Case Study of the Faculty Building in Singapore"

- **Authors:** Chien, S., Lee, J., & Su, Y.
- **Published in:** *Energy* (2020)
- **Summary:** This paper presents a case study where deep learning techniques were used to predict the energy consumption of a faculty building in Singapore. The study used Long Short-Term Memory (LSTM) networks to model and predict energy consumption based on historical data.

3. "Application of Machine Learning in Energy Management Systems"

- **Authors:** Zhang, M., & Wei, H.
- **Published in:** *Energy Procedia* (2019)



Ask anything

Nope

Nope

Nope

Only use AI with extreme caution, and make sure you double check all of its work.
You are responsible for what you submit.

Writing integrity

Deep Learning for Classifying Food Waste

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Abstract—One third of food produced in the world for human consumption – approximately 1.3 billion tons – is lost or wasted every year. By classifying food waste of individual consumers and raising awareness of the measures, avoidable food waste can be significantly reduced. In this research, we use deep learning to classify food waste in half a million images captured by cameras installed on top of food waste bins. We specifically designed a deep neural network that classifies food waste for every time food waste is thrown in the waste bins. Our method presents how deep learning networks can be tailored to best learn from available training data.

Index Terms—deep learning, neural networks, machine learning, food waste

The automatic classification of food waste in waste bins is technically a difficult computer vision task for the following reasons. a) It is visually hard to differentiate between edible and not-edible food waste. As an example consider distinguishing between eggs and empty egg shells. b) Same food classes come in a wide variety of textures and colors if cooked or processed. c) Liquid food waste, e.g. soups and stews, and soft food waste, e.g. chopped vegetables and salads, can largely hide and cover visual features of other food classes.

In this research, we adopt a deep convolutional neural network approach for classifying food waste in waste bins [9]. Deep convolutional neural networks are supervised machine

My Research Paper Grace Lindsay

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Writing integrity

Deep Learning for Classifying Food Waste

Amin Mazloumi:
Institute of Embedded S
Zurich University of Appli
Zurich, Switzerland
amin.mazloumian@zh

Abstract—One third of food consumption – approximately 1 every year. By classifying food waste, raising awareness of the measure significantly reduced. In this research, we classify food waste in half a million installed on top of food waste deep neural network that classifies food waste is thrown in the waste bin. How deep learning networks can be used to process available training data.

Index Terms—deep learning, food waste classification, food waste

Academic Disciplinary offenses include but are not limited to:

- cheating, plagiarism, falsification of data or sources, forgery of academic documents in attempt to defraud;
- destruction, theft, or unauthorized use of laboratory data, or research materials.

The following penalties may be imposed by the faculty for disciplinary infractions:

- Warning
- Disciplinary Probation
- Suspension
- Dismissal

Technically a difficult task to distinguish between food waste in a wide variety of forms, e.g., soups and sauces, can largely hide the three different

Writing integrity

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Technically not plagiarism, but bad writing!

Writing integrity

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My Research Paper
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According to Mazloumian et al. (2020), visually classifying food waste in bins faces three main challenges: distinguishing edible from non-edible waste, overcoming how diverse single food classes can be, and classifying images with liquid and soft waste that hide other waste classes. Here, I will test three different neural networks trained to classify food waste

Lovely!

Citations and references

Google Scholar

Deep Learning for Classifying Food Waste

Articles

About 76,900 results (0.18 sec)

Any time

Since 2023

Since 2022

Since 2019

Custom range...

Sort by relevance

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Deep learning for classifying food waste [PDF] arxiv.org

A Mazloumian, M Rosenthal, H Gelke - arXiv preprint arXiv:2002.03786, 2020 - arxiv.org

... **food waste** can be significantly reduced. In this research, we use **deep learning** to **classify food waste** in half a million images captured by cameras installed on top of **food waste** bins. ...

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[HTML] A Novel Model to Detect and **Classify** Fresh and Rotten Fruits to Reduce **Food Waste** Using a **Deep Learning** Technique

TB Kumar, D Prashar, G Vaidya, V Kumar - Journal of Food ..., 2022 - ...

... to be blamed for the majority of **food** that is **wasted**. Families are the **waste**, and we sought to reduce this by **identifying** fresh and damaged f

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[HTML] An Application of **Deep Learning** Models to Automate **Classification**

AZ Espinoza - 2019 - search.proquest.com

... are trained and evaluated on a novel **food waste** dataset to assist in a

... of **food** image **classification**, rather than the task of **food waste clas**

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[PDF] An efficient **classification** of kitchen waste using c techniques

APS Kumar, K Buelaevanzalina - Turkish Journal of Computer and ..., 20...

... removal of knives and chemical **waste**. • In this project we have to bui

different types of **waste**. We used transfer **learning** models to **classify** th

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Identification of **Food Waste** through Object Recognition [PDF] ieee.org

L Farinella, E Fernandes, N Michener... - 2020 11th IEEE ..., 2020 - ieeexplore.ieee.org

Put all full citations in the reference section.

×

Cite

MLA Mazloumian, Amin, Matthias Rosenthal, and Hans Gelke. "Deep learning for classifying food waste." *arXiv preprint arXiv:2002.03786* (2020).

APA Mazloumian, A., Rosenthal, M., & Gelke, H. (2020). Deep learning for classifying food waste. *arXiv preprint arXiv:2002.03786*.

Chicago Mazloumian, Amin, Matthias Rosenthal, and Hans Gelke. "Deep learning for classifying food waste." *arXiv preprint arXiv:2002.03786* (2020).

Harvard Mazloumian, A., Rosenthal, M. and Gelke, H., 2020. Deep learning for classifying food waste. *arXiv preprint arXiv:2002.03786*.

Vancouver Mazloumian A, Rosenthal M, Gelke H. Deep learning for classifying food waste. *arXiv preprint arXiv:2002.03786*. 2020 Feb 6.

BibTeX EndNote RefMan RefWorks

Project Timeline

Now - Start thinking about your teams and project ideas, look into data and methods.

Mar 6 - Project Plan Homework assigned

Mar 20 - Project Plan Homework due by the end of the day, feedback the following day
(teams cannot be changed after this point)

April 17 - In class project check-in

April 24 - In class project work time

May 1 - In class project presentations

May 8 - Project reports due

Exam Review

Exam will include multiple choice, T/F, and short answer questions

You will be tested on knowledge of climate change topics as well as machine learning topics

There will be questions about the papers we've read

You will not need to write code

To study for the exam:

For climate content, know:

- the basics of what is causing climate change
- where emissions are coming from
- changes we expect to happen as a result of warming
- basics of remote sensing
- SSPs

To study for the exam:

For ML content, know:

- basics of the simple regression models
- the basics of artificial neural networks
- what architectures are used for what tasks and why
- what loss functions are used for different problems
- what balanced data means
- pros and cons of different evaluation metrics
- validation/generalization
- types of data (image, time series, etc)
- Transfer learning, representation learning

To study for the exam:

Make sure for each of the papers we've read, you know:

- PMIRO answers

- The general architecture of the model used, what the inputs to the model were, any preprocessing discussed, what the output was, what the objective function was, how the performance of model was evaluated, what kind generalization did they test for

In all cases, focus on what was covered in class