



University
of Exeter

Environmental Intelligence
@ Exeter Research Network

Social and Computer Science: Interdisciplinary Conversations on AI

Tuesday 29th July 09:30-12:00

The Sky Deck, Innovation Centre Two





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Environmental Intelligence
@ Exeter Research Network

Programme

09:15	Arrival & coffee
09:30	Introductions
	Milto Miltiadou <i>Advancement of Earth Observation Algorithms for Forest Monitoring</i>
	Tristan Cann <i>AI and social science for climate communication</i>
09:45 5 min lightning talks	Patrick Gildersleve <i>The Web AI-pocalypse</i>
	Katie Ledingham <i>Responsible AI</i>
	Jack Reed <i>AI, horticulture and social science: An ongoing project</i>
	Frederico Botta <i>Understanding human behaviour in cities</i>
	Presentation Q&A
10:45	Coffee
11:00- 12:00	Collaborative discussion
12:00-12:30	Lunch

Environmental Intelligence





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Lightning Talks



Generated using playground AI



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Milto Miltiadou





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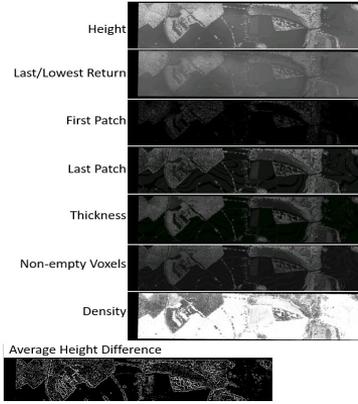
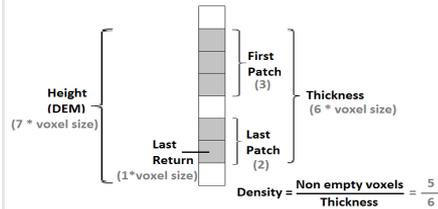
Department of Computer Science

Advancement of Earth Observation
Algorithms for Forest Monitoring

Milto Miltiadou, Lecturer in Computer Science (E&R)

Lightening Talks

DASOS



Index	centroid_x	centroid_y	V0_0_0	V0_0_1	V0_0_2	V0_0_3	V0_0_4	V0_1_0	V0_1_1	V0_1_2	V0_1_3	...
0	251836.109	6048994.5	7	14	10	26	0	0	9	10.25	11.875	...
1	251843.906	6048980.5	0	0	0	0	0	0	0	0	0	...
2	251846.312	6048979	9	60.75	70.75	13	8	0	0	0	7.667	...
3	251849.312	6049022.5	48.556	93.222	20.5	0	7	0	0	0	0	...
4	251851.703	6048988	100.2	53.222	10.5	7.143	0	0	0	0	47.25	...
5	251852.906	6048975	0	0	0	0	26.875	0	10.444	13.182
6	251857.109	6048974	0	0	0	0	45.667	93	16.333	7.25
7	251858.312	6049010.5	0	0	0	0	0	0	0	8	6	...
8	251860.703	6048984	0	45.75	8	7.333	0	0	0	0	6.8	...
9	251861.312	6049000	0	0	0	0	0	0	0	0	0	...

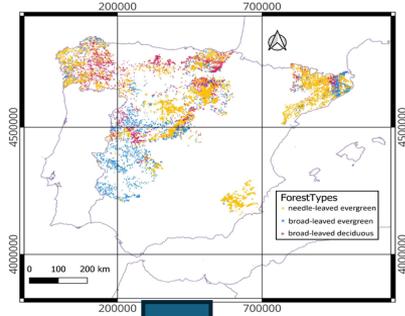
Index	centroid_x	centroid_y	Height_Middle_Column	Height_Mean	Height_Median	Height_Std	Sum_Int_Diff_X	...
0	251836.109	6048994.5	36	35.5	36	0.943	95.125	...
1	251843.906	6048980.5	19.8	20.1	20.4	0.671	0	...
2	251846.312	6048979	16.8	16	15.6	1.02	169.167	...
3	251849.312	6049022.5	36	35.7	36.6	0.964	169.278	...
4	251851.703	6048988	17.4	16.2	16.2	0.346	406.065	...
5	251852.906	6048975	27	26.4	26.4	0.917	68.537	...
6	251857.109	6048974	17.4	17.4	18	0.849	162.25	...
7	251858.312	6049010.5	40.8	40	39.6	1.02	251.36	...
8	251860.703	6048984	17.4	16.6	16.2	0.663	67.883	...
9	251861.312	6049000	19.8	20.1	20.4	0.671	0	...

Raw Voxel Intensities into a .csv file

Processed Info from that area (i.e. distribution of non empty voxels) into a .csv file

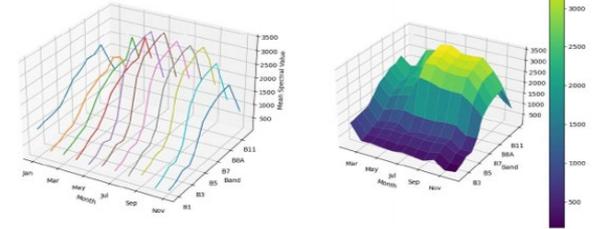


exports



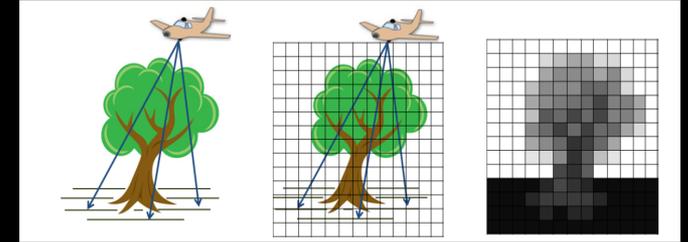
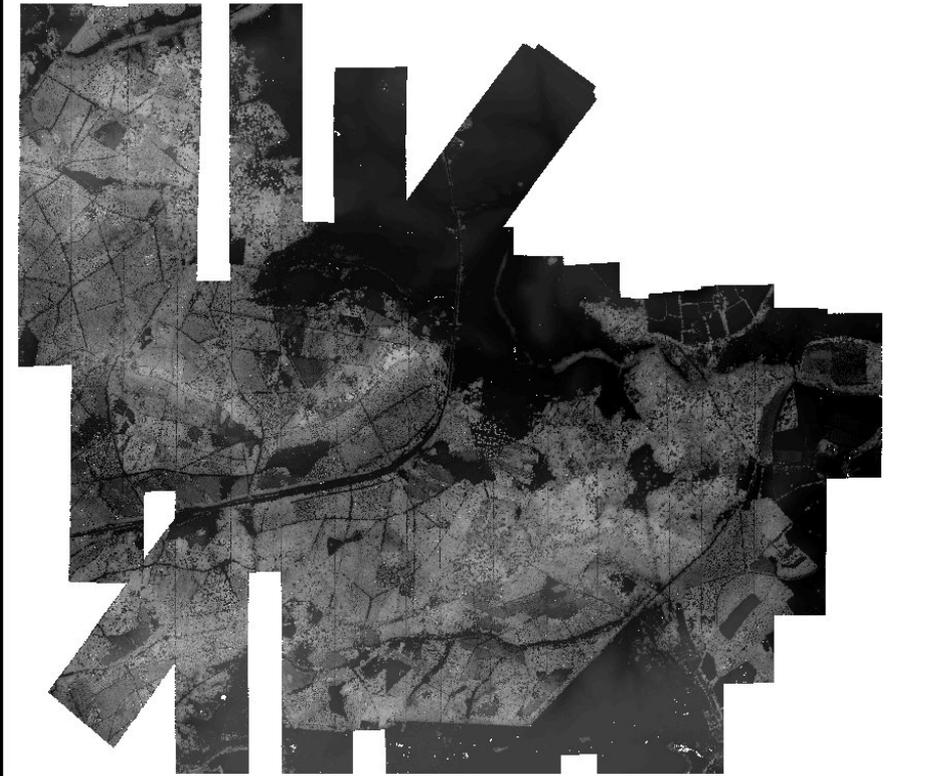
PlotToSat

Name	CX	CY	...	O_VHAsc	O_VHDes	...	O_B11	O_B12	...
MergedCvus	290926.7	4448817	...	-17.0553	-18.5423	...	2193.882	1397.258	...
featurevectorWORK_0	292002.7	4448824	...	-17.2603	-18.9425	...	2391.643	1582.035	...
featurevectorWORK_0	286925.8	4447683	...	-18.0058	-19.7285	...	2130.567	1443.824	...
featurevectorWORK_0	289845.5	4446749	...	-18.7253	-19.7959	...	1935.334	1244.396	...
featurevectorWORK_0	288876	4445730	...	-19.4511	-20.6621	...	2495.202	1675.776	...
featurevectorWORK_0	292879.1	4445809	...	-18.948	-19.8698	...	2831.004	1989.193	...
featurevectorWORK_00000000000000000005_S1_sho	295881.3	4445807	...	-18.1074	-18.26	...	2765.658	1938.781	...
featurevectorWORK_00000000000000000005_S2_sho	289932.3	4441763	...	-20.0205	-19.9085	...	2640.889	1830.741	...
featurevectorWORK_0000000006_0000000011_S1_sho	285901.6	4440807	...	-18.5204	-19.4258	...	2769.404	2078.274	...
featurevectorWORK_0000000006_0000000011_S1_sho	286923.5	4440811	...	-22.1995	-22.4506	...	2719.375	1888.035	...



Versatile tools for generating feature vectors for Machine Learning Applications

DASOS

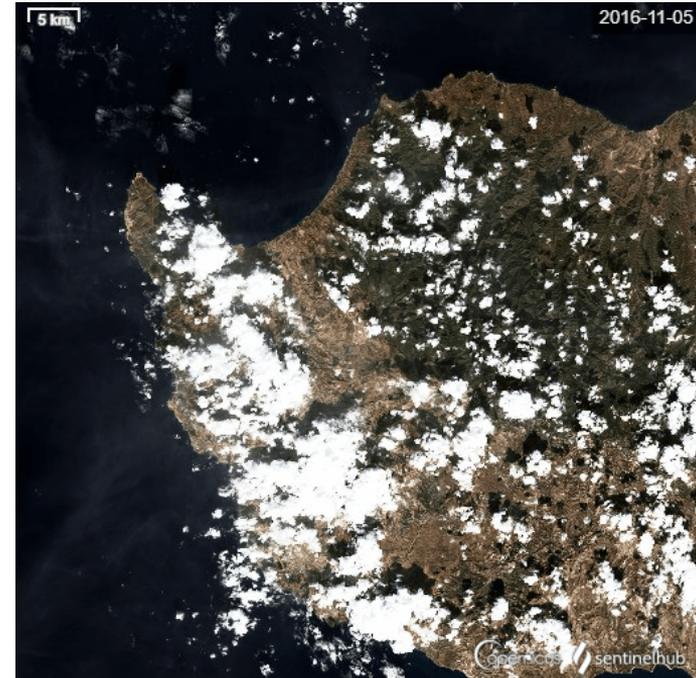


Manages both full-waveform and discrete LiDAR

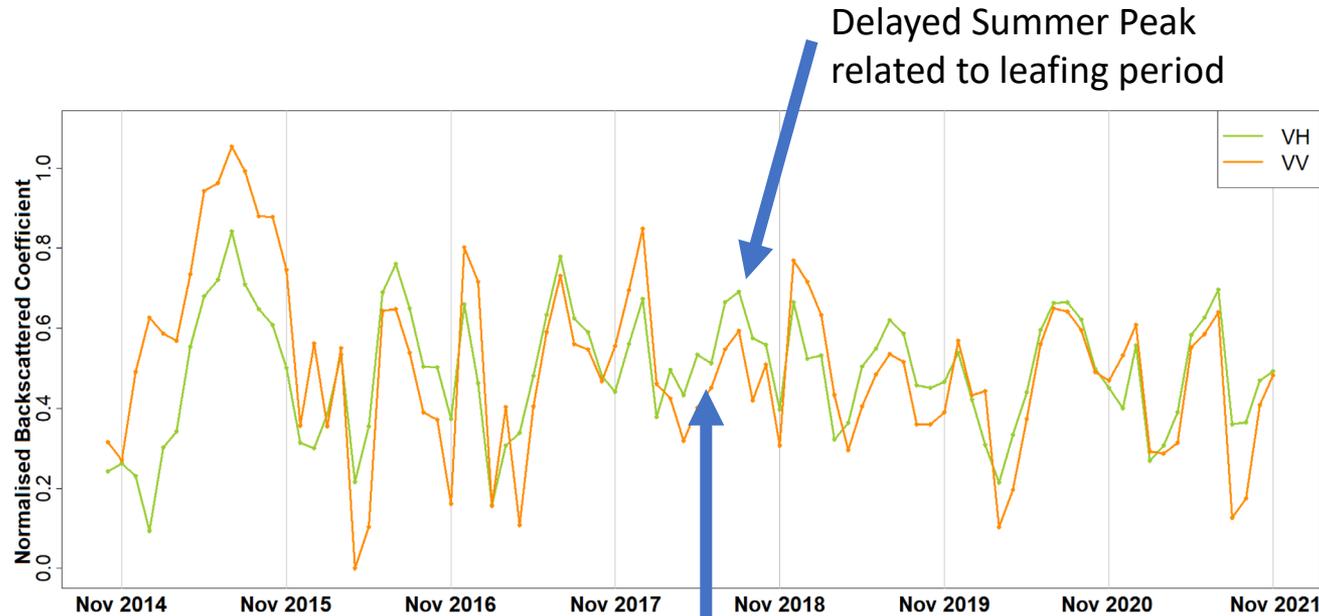
Addresses variations in point cloud density

Time-series of satellite data

If we get multiple satellite image and
order them according to time
=> we can observe how the earth
changes seasonally and over time



Associations between climatic conditions



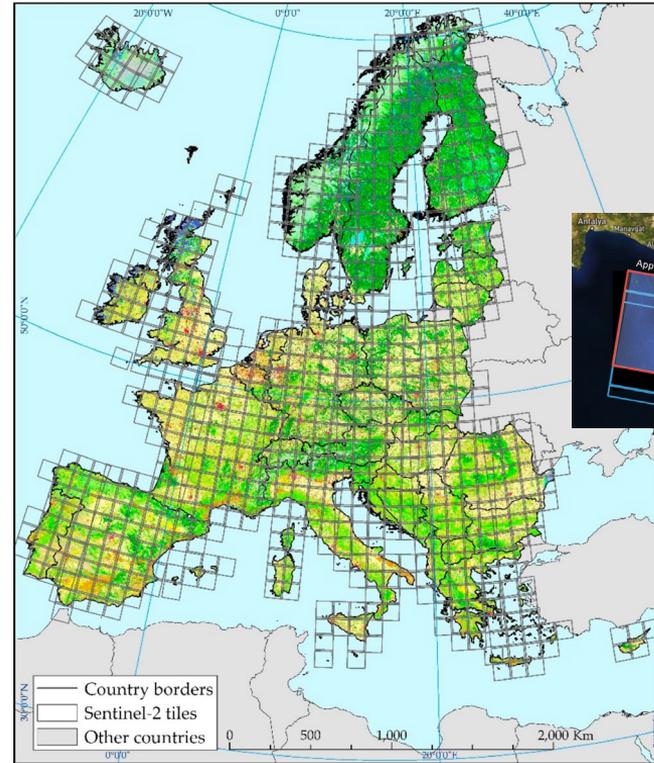
Warmer
Spring

Miltiadou, Milto, et al. "A comparative study about data structures used for efficient management of voxelised full-waveform airborne LiDAR data during 3D polygonal model creation." *Remote Sensing* 13.4 (2021): 559.

Pre-processing

- Extracting time-series analysis is challenging
- One year of Spanish data
 - ~ 2,700 Sentinel-1 images (estimated 2.5TB)
 - ~19,500 Sentinel-2 images(estimated 15.8TB)
- Google Earth Engine is a cloud-based geospatial analysis platform

Sentinel-2 image tiles



Sentinel-1 image tile



Available at (Accessed 04/04/24): <https://www.mdpi.com/2072-4292/12/21/3523>

PlotToSat (published version)

Streamlines the process of generating EO time-series

Take as input a plot network in

.csv format and a year

Extract Sentinel-1 and Sentinel-2

time-series of each plot

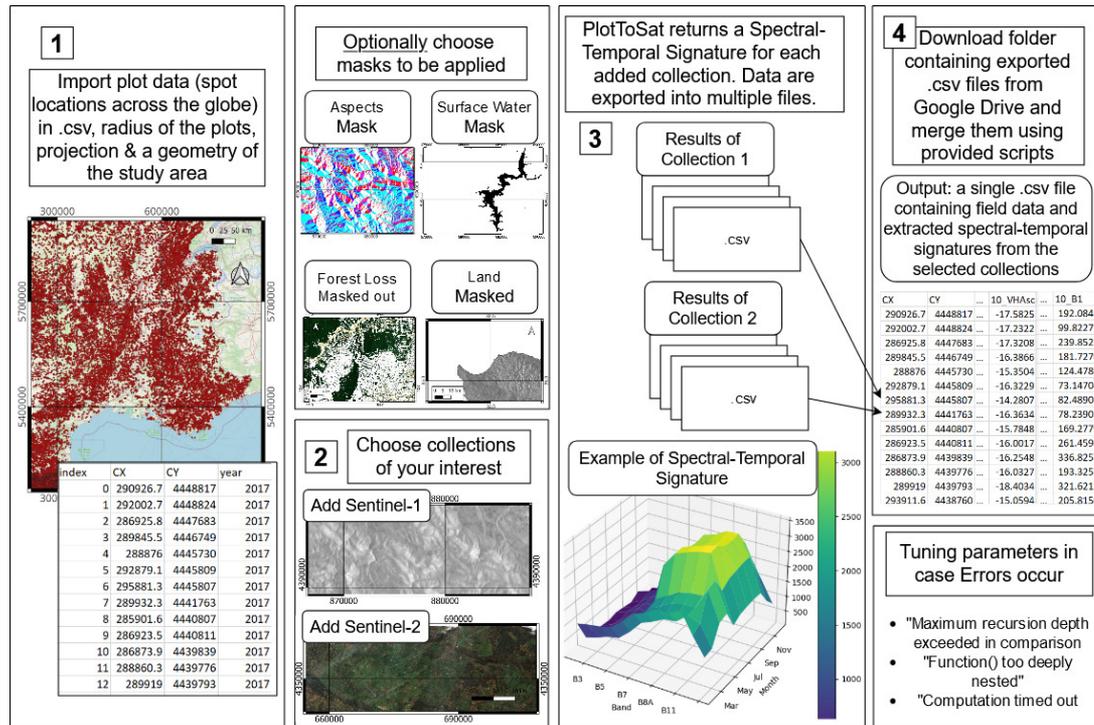
PlotToSat extracted time-series for ~16,000 plots using an

estimated of 18.3TB data within less than 24hours

Available at:

<https://github.com/Art-n-MathS/PlotToSat>

Uses the Google Earth Engine



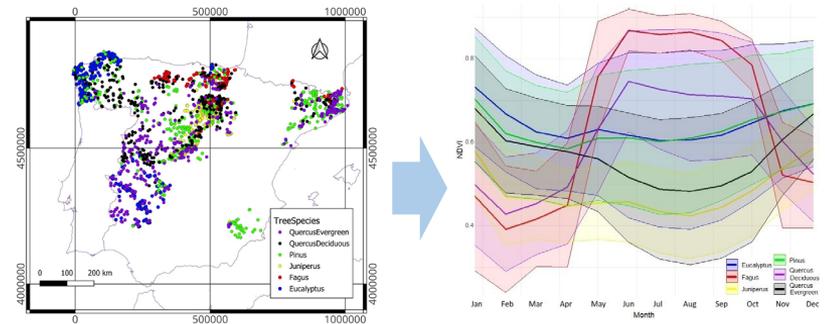
PlotToSat: A Tool for Generating Time-series Signatures from Sentinel-1 and Sentinel-2 at field-based plots for Machine Learning applications ng it easy to add new collections - *Environmental Modelling & Software*, Miltiadou, M. et al.

First Application of PlotToSAT: Tree genera classifications

- In test case 3, which uses all samples, the F1 score for small genera classes was low due to the unbalanced training/testing dataset.
- In test cases 1 and 2 that dataset was resampled for balancing, the F1 score for large genera classes was low due to the likely creation of uncorrelated subgroups within these classes, which were under-represented.
- Selection of the most important features as well as finding ways to account for the subgroups within the dataset shall improve classification results.

Table 2. Number of plots per genus used in each test case.

Genus class	No of 100% single genus plots	Number of plots		
		Test case 1	Test case 2	Test case 3
<i>Pinus</i>	5601	236	380	5601
<i>Quercus</i> (evergreen)	1941	236	380	1941
<i>Quercus</i> (deciduous)	1301	236	380	1301
<i>Fagus</i>	287	236	380	287
<i>Eucalyptus</i>	236	236	380	236
<i>Juniperus</i>	276	236	380	276

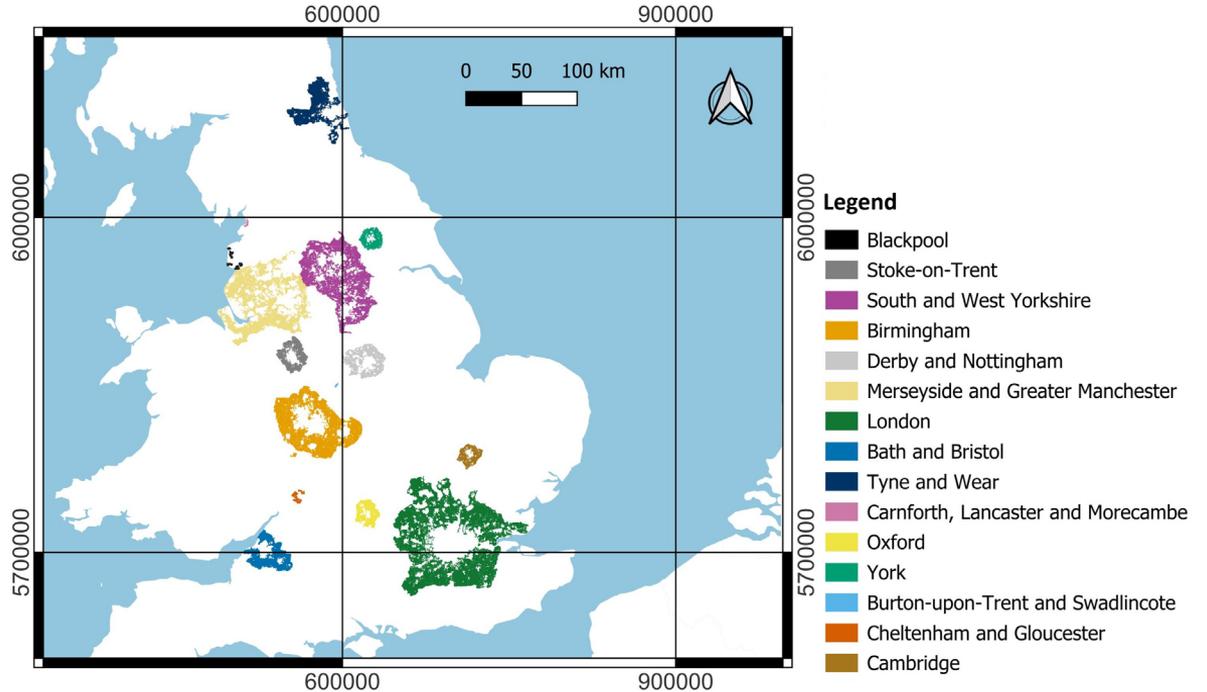


GreenSight Project with Met Office

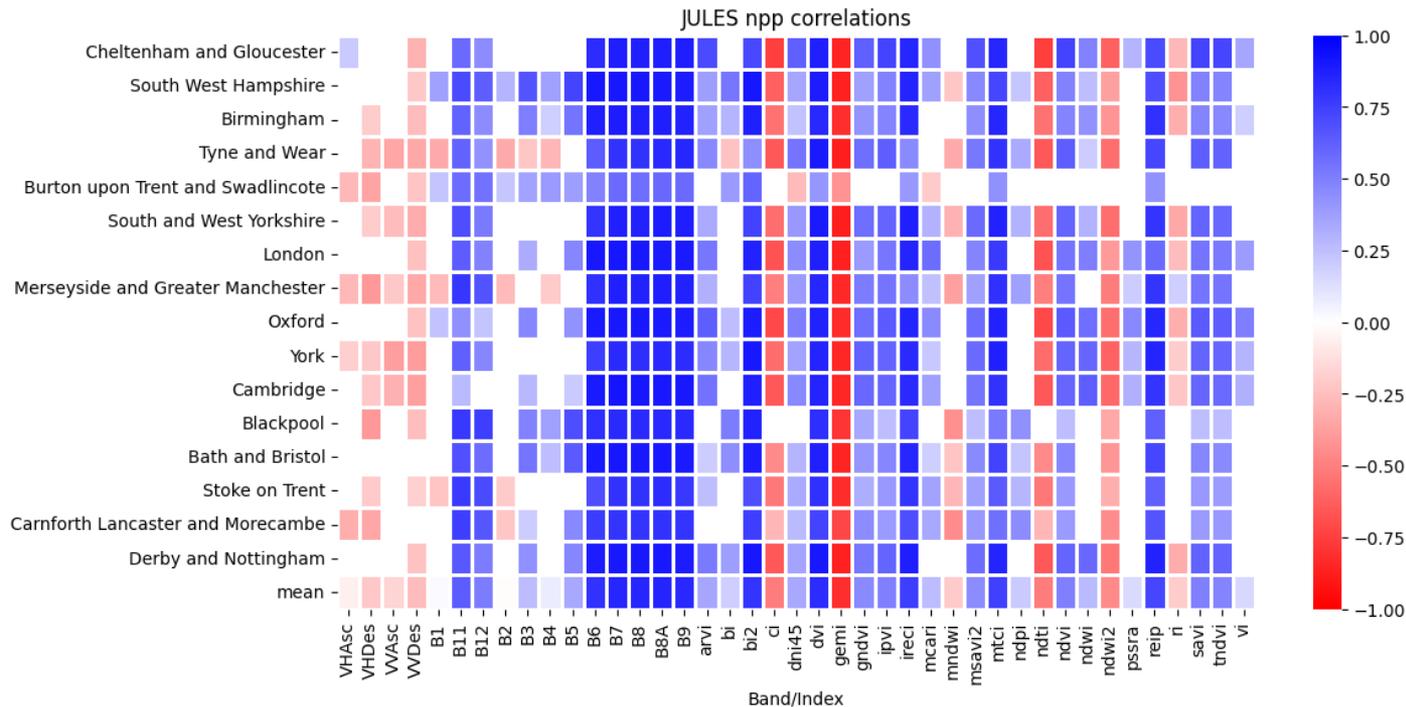
Comparison of carbon estimates from the JULES land surface model and Earth Observation time-series for UK Green Belts

PI: Hywel Williams & Edward Pope

Co-PI: Milto Miltiadou



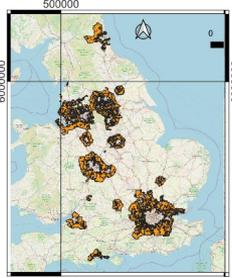
Preliminary Results – Net Primary Productivity



by Finley Gibson

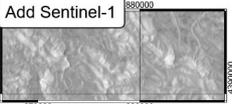
PlotToSat (new features)

1 Import shapefile containing multiple polygons of interest



2 Choose collections of your interest

Add Sentinel-1



Add Sentinel-2



PlotToSat exports a Spectral-Temporal Signature for Sentinel-2 and four time-series (VH/VV, descending/ascending) for Sentinel-1. The data are saved as multiple .csv files on Google Drive.

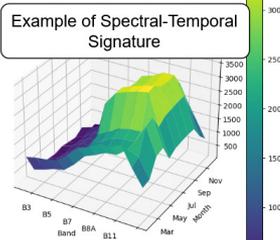
Results of Collection 1

3

Subset of .csv columns

9_VHAsc	9_VHDes	9_VVAsc	9_VVDes	LAD_CD
-16.3718	-16.3611	-10.4484	-10.2174	E07000197
-18.1447	-18.2323	-11.0223	-11.3199	E07000221
-17.1305	-18.2019	-10.0498	-11.2112	E07000196
-17.577	-17.828	-10.4872	-11.0749	E08000030
-18.0344	-18.0585	-10.7328	-10.9308	E07000222
-17.0008	-17.1209	-10.3168	-10.3062	E08000031
-17.5767	-17.691	-10.6825	-10.7419	E07000237
-18.2747	-18.2016	-10.7973	-10.9286	E07000238
-17.6058	-17.7044	-10.5057	-10.8136	E07000235

Example of Spectral-Temporal Signature



PlotToSat has been expanded to support

- the extraction of time-series at multiple regions/polygons defined in Shapefile
- of soil, water and vegetation indices has been added
(subset of Radiometric Land indices provided by ESA: <https://step.esa.int/main/wp-content/help/versions/9.0.0/snap-toolboxes/org.esa.s2tbx.s2tbx.radiometric.indices.ui/OperatorsIndexList.html>)

MSc Projects using PlotToSat



Forest Types Classification – Oliver Appleby

Land Cover Change for UNESCO site protection – James Chamberlain

Forest Types Classification – Oliver Appleby

Land Cover Change for UNESCO site protection – James Chamberlain

GW4+ PhD
Mapping Geohazard Proximity and
Risk Trends Around UNESCO
Heritage Sites

Upcoming

Projects



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ForestFireAI

PI - 260,348GBP

Large-scale Prediction of Forest Fire

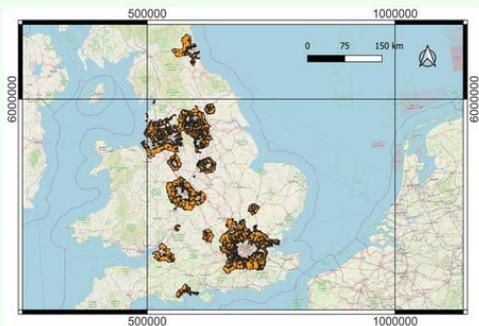
Drivers from Space Using Multi-source

Remote Sensing Data and Artificial

Intelligence

STARTING IN 2026

Past Projects



GreenSight

Co-PI - 89,480GBP

Earth observation data for greenbelt, carbon modelling and digital twins

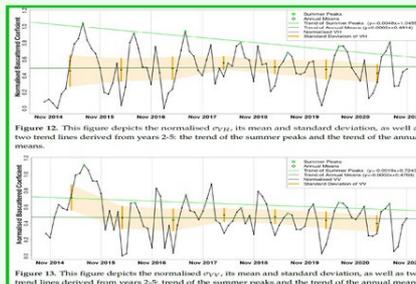
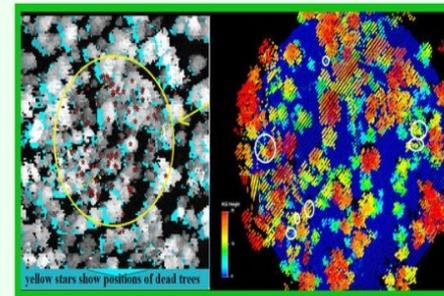


Figure 12. This figure depicts the reconstructed ν_{12} , its mean and standard deviation, as well as two trend lines derived from years 2-5: trend of the summer peaks and the trend of the annual means.

ASTARTE

250,000EUR

Analysis of SAR and thermal satellite data time-series for understanding the long-term impact of land surface temperature changes on forests



yellow stars show positions of dead trees

FOREST

150,000EUR

Advancement of tree structure observation algorithms for forest monitoring with LiDAR data

Thank you! Any Questions?

“Milto Miltiadou appears to be a researcher specializing in data analysis and machine learning applied to Earth observation, particularly focused on forests.” by Gemini 😊

email: m.miltiadou@exeter.ac.uk





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AI and social science for climate communication

Tristan Cann

Using semantic similarity to measure the echo of strategic communications

Research | [Open access](#) | Published: 12 March 2025
Volume 14, article number 20, (2025) | [Cite this article](#)



Visual portrayals of fun in the sun in European news outlets misrepresent heatwave risks

Saffron O'Neill ✉, Sylvia Hayes, Nadine Strauß, Marie-Noëlle Doutreix, Katharine Steentjes, Joshua Ettinger, Ned Westwood, James Painter

First published: 18 October 2022 | <https://doi.org/10.1111/geoj.12487> | Citations: 4

Computer Science



Social Science

{'score': 0.8562073111534119, 'label': 'other hob'}



Computer-assisted classification of contrarian claims about climate change

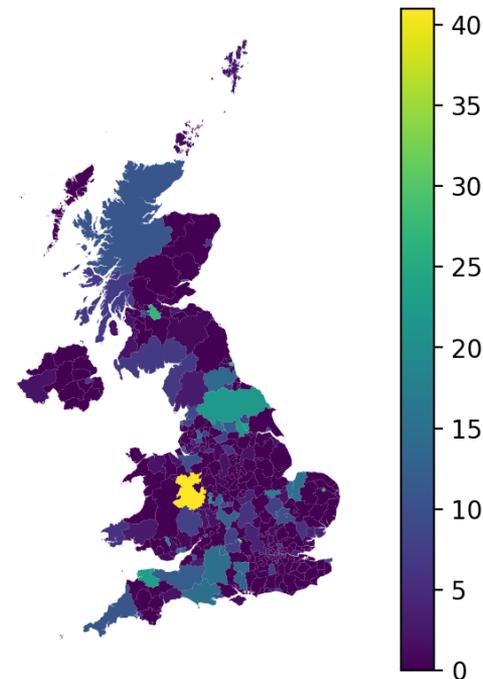
[Travis G. Coan](#), [Constantine Boussalis](#), [John Cook](#) ✉ & [Mirjam O. Nanko](#)

[Scientific Reports](#) 11, Article number: 22320 (2021) | [Cite this article](#)



Local News Map

A project to map out all of the UK's professional providers of local news.



Climate emergency and councils



The Web AI-pocalypse

Patrick Gildersleve

A  *The Atlantic* Sign In

It's the End of the Web as We Know It

A great public resource is at risk of being destroyed.

By Judith Donath and Bruce Schneier

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FUTURE

What is BBC Future? Earth More 

INTERNET

Is Google about to destroy the web?

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Intelligencer

Leaders | A tragedy of the digital commons

To survive the AI age, the web needs a new business model

Artificial intelligence has undermined the internet's central bargain

SCREEN TIME

AI Ate the Web. Now It's Coming Back for Seconds.

 *By John Herrman, a tech columnist at Intelligencer* 

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AI · GOOGLE

Google's AI Overviews are cutting off the oxygen to the web

BY BEATRICE NOLAN

Business | World wide worries

AI is killing the web. Can anything save it?

The rise of ChatGPT and its rivals is undermining the economic bargain of the internet

Love Father & Mother Bless You
Suggested for you · 2d · 🌐

Made it with my own hands! 😊
Thanks to everyone who appreciates this ❤️👍🙏🙏



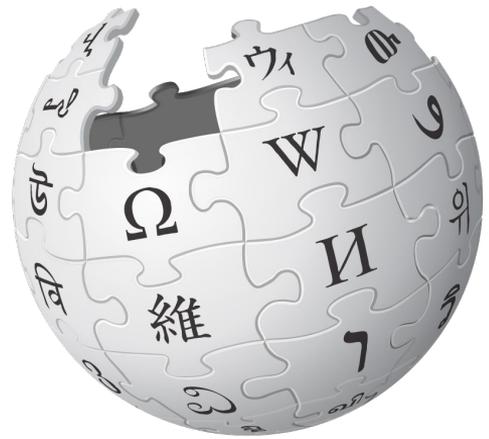
👍❤️👍 185K

2.7K comments 445 shares

-  Amen
2h Like Reply
-  Roy Cabigon
Amen
7h Like Reply
-  Janger E. Morris
Amen
6h Like Reply
-  Sigda Kesha Mae Zervalo
Amen
10h Like Reply
-  TallerTaller Momolu
AMEN 🙏👍👍❤️
4h Like Reply
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1d Like Reply
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-  Faith Smart Ogbemudia
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-  Lucy Thomas
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6h Like Reply
-  Willie Suratos
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-  Yoly Menjivar
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5h Like Reply
-  Kindness Shokuwushimi Bitrus

Wikipedia

- Wikipedia is a key example for LLMs relation with the digital commons
 - Computationally accessible, permissive data practices, high quality structured information
- And yet, **no citation, credit, or compensation**
- Readers and editors may be pulled away from Wikipedia – damaging LLM source data and a public good (Wagner & Jiang, 2025)
- What of Wikipedia’s various biases being integrated into LLMs? (Reagle & Rhue, 2011; Graham et al. 2014),

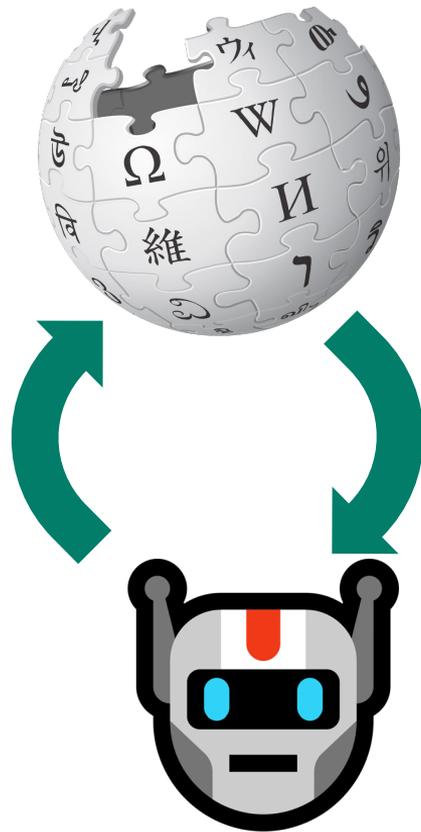


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The Critical AI Centre

LLM as Editor

- LLM tools are now being turned back on the very data from which they are trained
- Writing assistants for editing Wikipedia, fully bot editors
- What does this mean for Wikipedia?
- What does this mean for LLMs? → Model Collapse?



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AI in collaboration / conflict

- Simple bots have long existed on Wikipedia
- Shown to collaborate and conflict – even “edit war” (Tsvetkova et al., 2017)
- How might this new generation of AI bots interact with each other and humans?
- Detection is difficult, deployment is unethical
- Proposal: **Simulate Wikipedia**



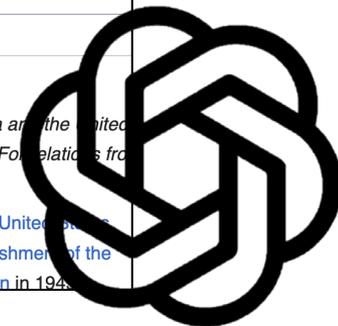
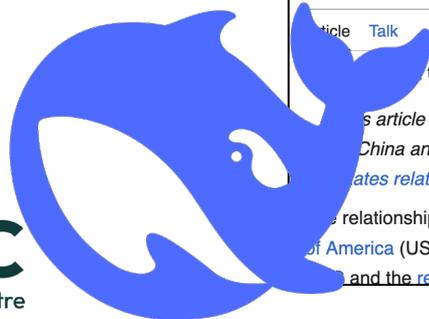
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Simulating Wikipedia

- Allow 100s/1000s of AI agents to edit an offline copy of Wikipedia
 - Give choice of articles, options to “revert” edits, memory of past actions?
- What models? What base prompts?
 - *“You are a Wikipedia editor. You will receive source wikitext for the Wikipedia article on _____ and can make any edits as you see fit (including no edits). Also provide a summary of your edits or the reason(s) no edits were made”*



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Preliminary Observations and Future Work

- “Lazy” summarizing
- Some rather pointless rephrasing, and rephrasing, and rephrasing...
- Language on contentious issues is sanitised and **not reverted** – sycophancy bias
- What (emergent) dynamics are seen at larger scales and different model specs?
- How do human-bot interactions affect content?



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Takeaways

- The Web is under threat – especially free, open resources
- Dangers from extractive use – pulling away readers, customers, contributors
- Dangers from poisoned contributions – possibly leading to model collapse
- We need to figure out the consequences before it's too late – advise on model capabilities, safeguards, regulation etc.



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CrAIC
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Katie Ledingham



Where Responsible Innovation (RI)
&
AI Meet

Dr Katie Ledingham
Senior Lecturer in Responsible & Transformative Innovation
Centre for Responsible Innovation & ITE
University of Exeter Business School

K.A.Ledingham@exeter.ac.uk

RI = Interdisciplinary field blending social science theory and methodology with practical and normative concerns in policy making

1. Delimit harm & unintended consequences
2. Align with societal values (in participatory ways)



OECD

Topics Co

OECD > Topics > Responsible Innovation

Responsible innovation

Responsible innovation is trustworthy technology development guided by democratic values, responsive to social needs and accountable to society. Adopting a responsible innovation approach in the development of emerging technologies can help align research and commercialisation with societal needs.

Policy sub-issue



UK Research and Innovation

Home > Manage your award > Good research resource hub > Responsible Innovation

Responsible innovation

Responsible innovation is a process that takes the wider impacts of research and innovation into account. It aims to ensure that unintended negative impacts are avoided, that barriers to dissemination, adoption and diffusion of research and innovation are reduced, and that the positive societal and economic benefits of research and innovation are fully realised.



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Home

Research and analysis

The Model for Responsible Innovation

The Model for Responsible Innovation is a practical tool created to help teams across the public sector and beyond to innovate responsibly with data and AI.

From: [Department for Science, Innovation and Technology](#)
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At core of RI – concept of **epistemic diversity** – drawing together diverse knowledges in the *design, development & deployment* phases

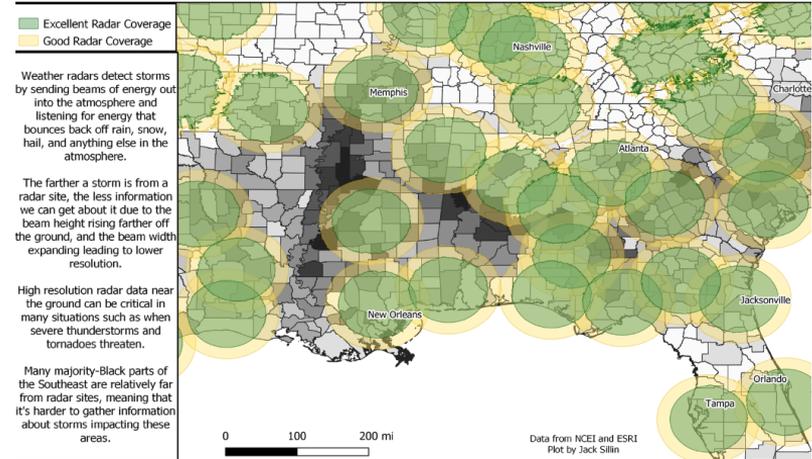
Anticipate, identify and mitigate against harms and issues upstream e.g., spatial, temporal and other biases within datasets

The politics of data labelling; model norms

RI focus is not just on tech design – but broader governance and institutional environments within which innovation developed & deployed e.g., Seattle earthquake prediction deployment
Social sciences – render tractable

Not just harm avoidance– but aligning innovation with societal values; political ecologies

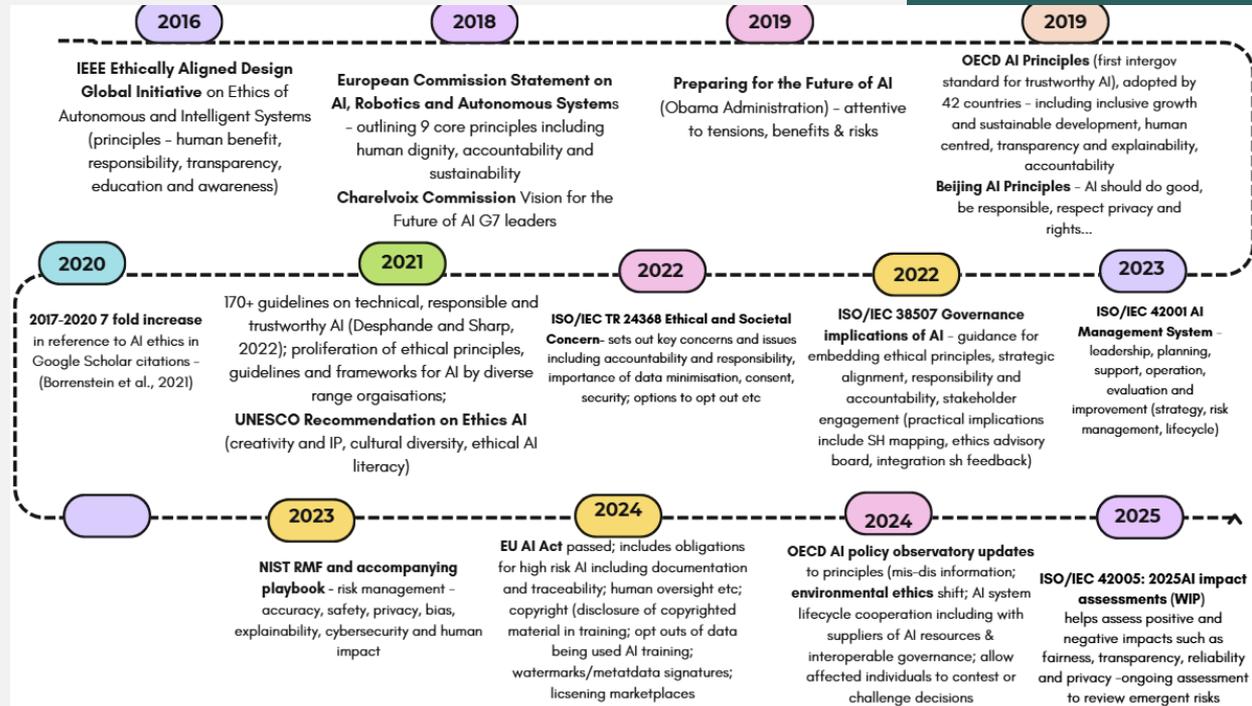
Are Black Americans Underserved by the NWS Radar Network?



Source: Sillin et al., 2021 in McGovern

Centre for Responsible Innovation - RAI

- 2016 - 200+ guidelines on responsible and trustworthy AI = profusion of ethical principles, frameworks and documents
- RAI – attempt to operationalise high level principles (fairness metrics and tools for bias detection; privacy safeguarding)
- BUT – we're at a crossroads moment –
- 'Ethics washing' is a term that continues to gain salience – described by Floridi (2019) as liberal borrowing from a plethora of frameworks that yields easily implementable norms



Two Example Illustrative Issues:

1. Narrow focus on risk rather than impact and implications more broadly defined
2. Narrowing of inclusion practices: industry survey only 11% engaged affected non-users; 4% generate public in SHE – limited harms articulated (harms without financial implications neglected) (Kallina et al., 2025)

RI for AI – seeks to address these gaps – interested in the processes and practices that can help innovation to avoid harm and do good (while recognising that notions of ‘good’ and ‘harm’ are always contextually contingent)

Rethinking AI Risk: Acoustic Monitoring in Care Homes

AI risk is often narrowly defined in terms of system accuracy, data security, or legal compliance (e.g. GDPR). Yet harm can be relational, cultural, and cumulative – and not easily captured by these metrics. Overreliance on tech may shift care from being relational and proactive to reactive and transactional. Engaging with diverse expertise and lived experience – from frontline staff, residents, and disciplines like sociology and anthropology – helps bring to light hidden risks and supports more responsible AI.



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Jack Reed



AI and Horticulture

An ongoing project

Dr Jack Reed (ESI and LEEP)



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How does artificial intelligence interact with place-sensitive* nature recovery?

*A place-sensitive approach recognises and builds on the diversity of places and supports policymaking that meets the needs of everyone.



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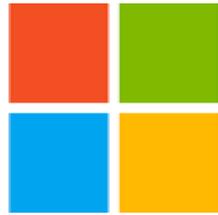


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Key partners



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Fieldwork

Qualitative methods

Visual analysis of AI infrastructures

Thematic content analysis from the garden's appearance on the BBC



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Findings

“It remains to be seen how much technology is going to help or possibly even hinder our lives in the garden. Although I have to confess, the more hands on it is, the better I like it” (Monty Don)



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New ways to engage with nature

Public facing metrics,
facilitated by AI analysis

AI enhances transparency
and accountability

AI facilitating a
conversation with the trees



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Meet the trees



Mespilus germanica
Common Medlar

Start TreeTalk

Tree growth
-6.0 $\mu\text{m}/\text{day}$
Low Growth

Humidity
56.0%
Normal Humidity

Tree temperature
17.0 °C
Normal Temp

Lean angle
14.6°
Normal Lean



Flowers & fruit

Solitary 2-3 cm white to pale pink, five-petaled flowers in late spring; flattened, reddish-brown pomes, soften ("blet") before eating.



Bark

Grey-brown bark developing deep vertical fissures that form flaky, rectangular plates over orange-brown inner bark.



Stems

Slender young shoots pubescent with small lenticels, maturing to smooth grey-brown stems; wild forms often bear spines.



Leaves

Deciduous, elliptic 8-12 cm leaves with finely serrate margins; glossy dark green above, densely hairy pale underside; autumn foliage turns bronze-red.



Thank you!
Questions and discussion

If a tree falls in the woods and nobody is around to hear it, does it make a sound...?



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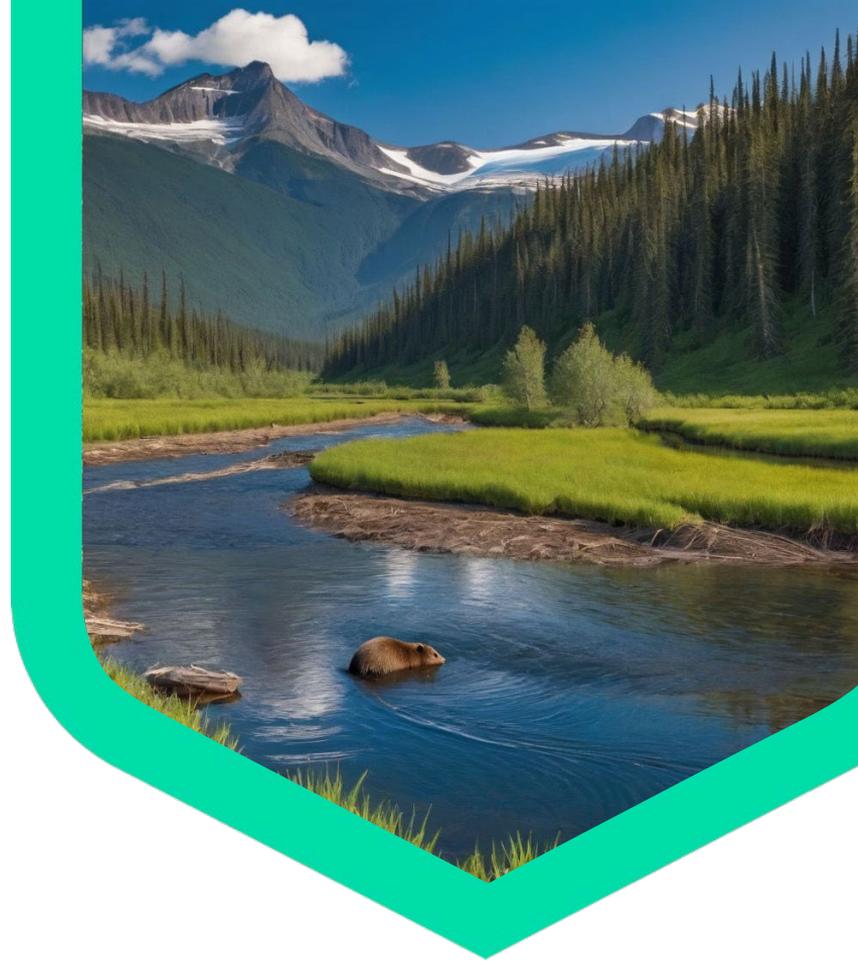
Frederico Botta





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Presentation Q&A





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Environmental Intelligence
@ Exeter Research Network

Collaborative discussion



Collaborative Discussion – Groups of 4-5

1. One idea that challenged or expanded your thinking

“Which presentation or idea from earlier made you think differently — or helped you see your own work in a new light?”

2. One issue in AI and society that feels urgent or overlooked

“What’s one issue in the AI–society space that really matters to you — either in your field, your research, or more broadly?” Why is this issue important, and what do you think needs to happen next?

3. In your groups where do your concerns, interests, or methods overlap — even if you approach them differently?

Is there anything that would be interesting to explore together further?

4. What makes collaboration across disciplines difficult — and how might we make it easier?

Are there language barriers, assumptions, or expectations that get in the way? What would help you stay connected to people in other fields beyond today? How do we continue this conversation beyond the event?



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Next steps

Environmental Intelligence

