AI for Nature & Environment: Bad tech, AI, and nature-based solutions

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"AI for Nature" – good intentions
.. but what could go wrong?

1. "Bad" tech?
   1.1 (a) Bad side-effects
   1.2 (b) Ineffective tech: factors limiting impact
2. Global solutions? (...ie rich world only)
3. Nature-based solutions

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We've already encountered:

- CO_2e emissions *see (Elec cost-benefit)*
- e-waste *(see: Devices)*
- Wildlife disturbance *(see: Biologging)*

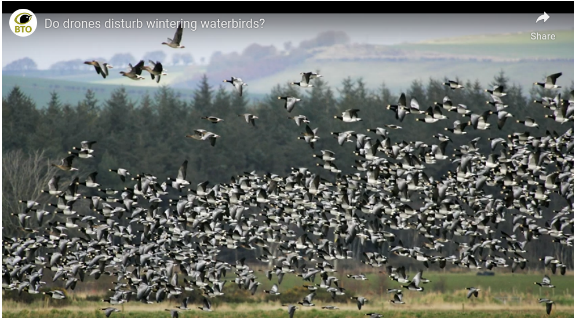
Weigh up the costs versus benefits.
Side-effects not always obvious.

Wildlife disturbance

- **Tagging/catching** animals may alter behaviour, or even reduce life-chances (keep tag weight $< 5\%$ body-mass)
- **Static devices** (camera traps / acoustic monitors) less disturbance than in-person surveys (such as **smartphone citizen science**)
- **Remote sensing**: no disturbance...

Wildlife disturbance: Drones

Do drones disturb birds? Predator-like



Jarrett et al (2020)

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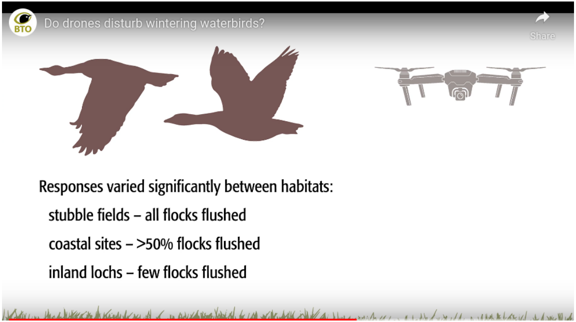

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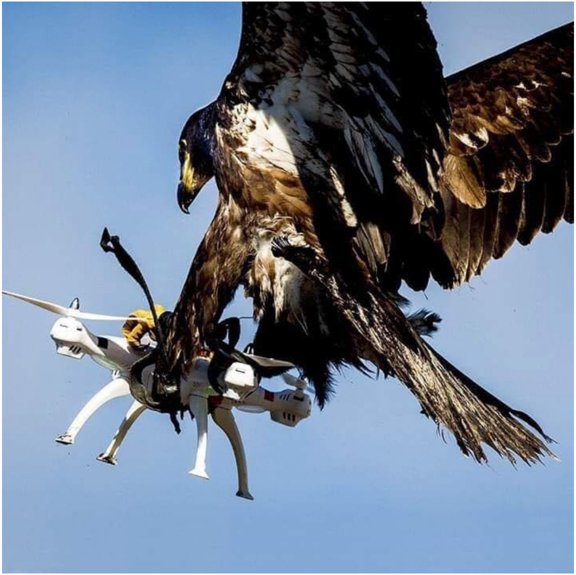

(Police exercise, Katwijk, March 2016)

Information for bad actors

Public information about species location (e.g. GBIF)

→Info for trophy-hunting, poaching, stealing eggs?
→Hide details for at-risk species, or delay info release

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Machine learning workflow:

train → validate → test

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Do your ML results *generalise* well?

Performance on the **test set** is
an estimate of performance 'in the wild'

...but it is limited to the data you were able to collect
Conditions differ in the wild: weather, smartphones, usage...

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Systemic limitations: Rebound effect

Even if the tech *works, without side-effects, and is used,* other factors may limit its impact

1. **Rebound effect:**
   Systems/people adjust to improvements
   $\rightarrow$Reduced overall benefit
2. **Jevons paradox:**
   Increased efficiency $\rightarrow$People use more
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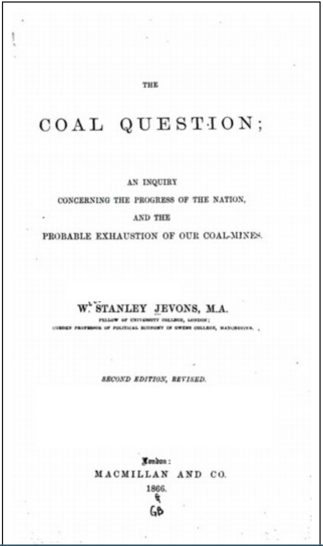
Jevons paradox


THE

COAL QUESTION;

AN INQUIRY
CONCERNING THE PROGRESS OF THE NATION,
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PROBABLE EXHAUSTION OF OUR COAL-MINES.

W. STANLEY JEVONS, M.A.

SECOND EDITION, REVISED.

London:
MACMILLAN AND CO.
1866.

Jevons (1865)
"The Coal Question; An Inquiry Concerning the Progress of the Nation, and the Probable Exhaustion of Our Coal Mines"

Rebound effect / Jevons paradox

(These numbers are fictional)

60W

6W

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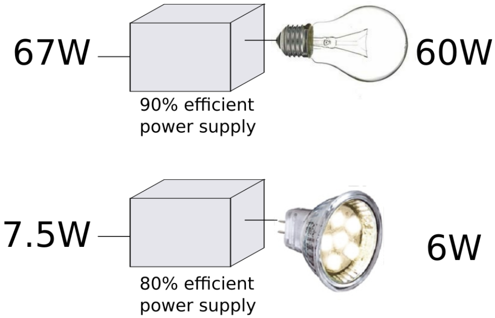

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Information for bad actors (Part II)

Public information about monitoring,

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→Bad actors can evade detection

Potential rebound effect

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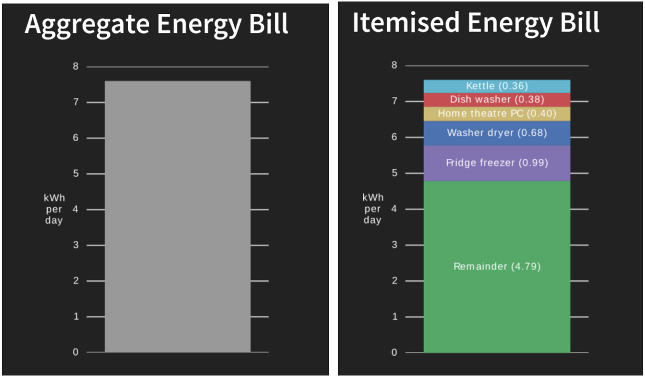
Behaviour: will nudges work?

"Nudge theory": small/mild interventions might predictably lead to preferred behaviours

> *"80% of our hotel guests re-use their towels"*

Behaviour: energy disaggregation

Application of ML: energy 'disaggregation'
Infer *which appliances* are in use



(Kelly 2016)

Visualise energy use →Users can make better choices

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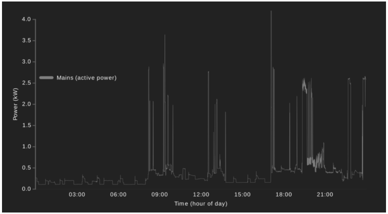

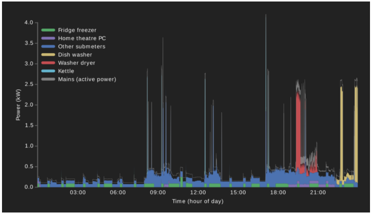

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Visualise energy use →Users can make better choices

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Does this feedback change domestic energy use?

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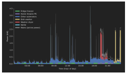
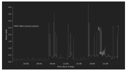
  - Average 4.5% reduced energy use 
  - But basic 'aggregate' feedback gives 3% reduction 
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Recommendations: improve the intervention; or try something else.

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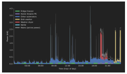
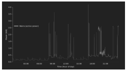
    - Average 4.5% reduced energy use 
    - But basic 'aggregate' feedback gives 3% reduction 
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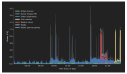
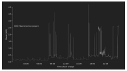
  - Average 4.5% reduced energy use 
  - But basic 'aggregate' feedback gives 3% reduction 
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FIGURE 2. Before and after example of the transformation carried out by our GAN approach, based on an image of a suburban house.

Luccioni (2021)
"Using Artificial Intelligence to Visualize the Impacts of Climate Change"

"Public awareness and concern about climate change often do not match the magnitude of its threat to humans and our environment. One reason for this disagreement is that it is difficult to mentally simulate the effects..."

?

Behaviour

All is not lost!

Nudges and behaviour changes can be effective

But: be careful with assumptions about how people will respond to a technology in use

Factors limiting impact

We've considered: side-effects; ML that doesn't generalise; rebound effect; Jevons paradox; info for bad actors; behaviour-change uncertainties.

Q: Which methods we've seen are vulnerable to these risks?

- Solar forecasting
- Mapping species detections
- Flood prediction
- Biologging
- Automatic dangerous animal detection
- Smartphone wildlife ID
- Detecting greenhouse gases from space
- Climate policy tracker
- Satellite land-use mapping
- ...

—

Global solutions?

Many tech-based solutions might be ‘rich-world only’
Q: Why?

Transport: self-driving cars?

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- Many smartphones, constantly connected high-qual wifi
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- ‘Data-rich’ countries (see next slide)

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Data-rich / data-poor countries

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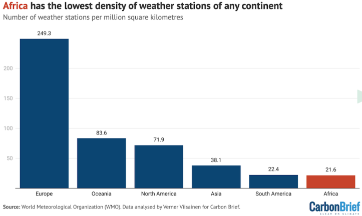
is hi-res data available?

- Geographic remote sensing: Satellite vs plane
- Weather stations per km^2:



Training ML: datasets collected in the rich world →ML low performance in poorer areas

- "How ImageNet Misrepresents Biodiversity" Luccioni et al (2022) (Lec 2)
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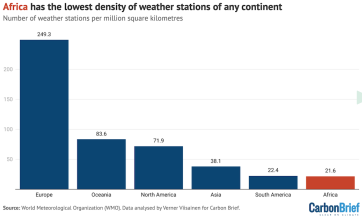

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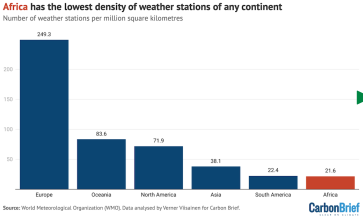

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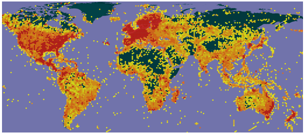


How to make solutions global?

1. Use available tech (e.g. smartphones widespread, but not high-bandwidth internet)
2. Publish open data
   - Global satellite remote-sensing data (e.g. NASA/EU)
   - Crowdsourced solar panels (OpenStreetMap)
   - Species observations (GBIF)
   - Publish **ML outputs** e.g. land-use estimates
3. Collaborate to improve datasets
4. Work with users / stakeholders

“Nature-based solutions”

Nature-based solutions: “use of natural features and processes to tackle socio-environmental issues.”
2 general benefits:

1. less enviro cost to implement;
2. often *positive* side-effects/synergies of biodiversity benefits.

Consider: planting trees versus CO2-removal tech

AI and Nature-based solutions

"AI is not the solution
... but AI can help implement/monitor the solutions"

- Forest management, rewilding
  $\rightarrow$Support with remote sensing
- Understand animal behaviour and populations
  $\rightarrow$Successful reintroductions

Q: Other examples?

Managing protected areas with RL

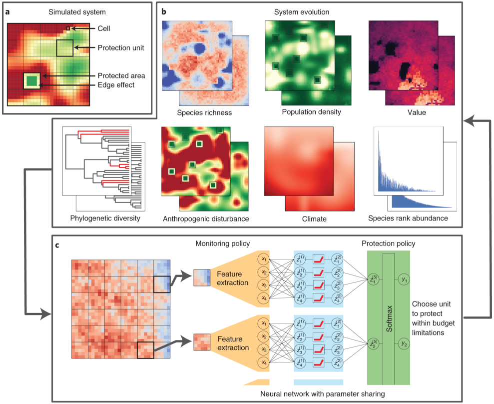
Reinforcement learning

Managing protected areas with RL

- Reinforcement learning
  - ML to decide which actions to take

Managing protected areas with RL

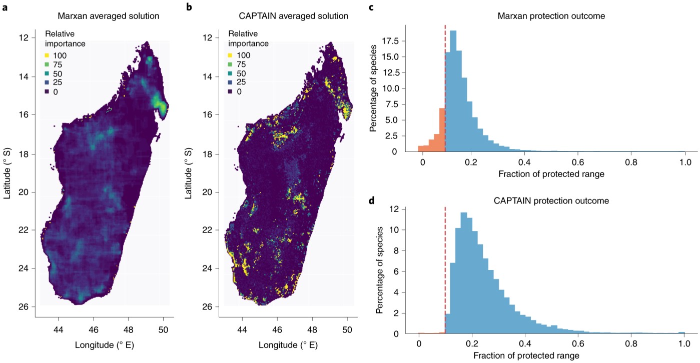
Goal: decide **which areas of land** to protect (e.g. nature reserve)



Silvestro (2022)

Managing protected areas with RL

Results:



Silvestro (2022)

Concluding

Tech solutions: route to impact is complex

All is not lost!

Some solutions are more robust to these issues than others

Lessons:
1: Consider whether your ML will really generalise
2: Beware of assumptions about behaviour
3: Be conscious of side-effects and feedbacks

Summary

1. What could go wrong?
   1.1 (a) Bad side-effects: CO2e, e-waste, disturbance, info for bad actors
   1.2 (b) Ineffective tech / factors limiting impact:
       - ML generalisation
       - Rebound effect and Jevons paradox
       - Behavioural impacts uncertain
2. Global solutions? Rich world only?
   - Costs of devices or compute-power; volunteer spare time; data-rich countries; ML trained from rich countries' data
3. Nature-based solutions

Next steps

Lab:

- Individual project development

Next time:

- Data viz / data mining