

Carbon dioxide removal

Biological and Chemical

Assignments

Brightspace discussion question:

“How concerned are you about the impacts of climate change in your lifetime?”

Due this Friday by 5pm.

Third programming assignment on identifying crops in remote sensing data

Due Friday the 3rd by midnight. **Correction posted**

Midterm - March 9th (review on Mar 2)

Climate change in the news

Climate change in the news

Hina Battery becomes 1st battery maker to put sodium-ion batteries in EVs in China

By [Lei Kang/CnEVPost](#)

February 23, 2023 14:15 GMT+8



Battery maker Hina Battery today unveiled three sodium-ion battery cell products and announced a partnership with Anhui Jianghuai Automobile Group Corp (JAC), which has made one of its models the first to carry sodium-ion batteries.

Hina Battery and Sehol -- a joint venture brand between JAC and Volkswagen Anhui -- have jointly built a test vehicle with sodium-ion batteries based on the latter's Sehol E10X model.

The test vehicle has a battery pack with a capacity of 25 kWh and an energy density of 120 Wh/kg. The model has a range of 252 km and supports fast charging of 3C to 4C. The battery pack uses cells with an energy density of 140 Wh/kg.

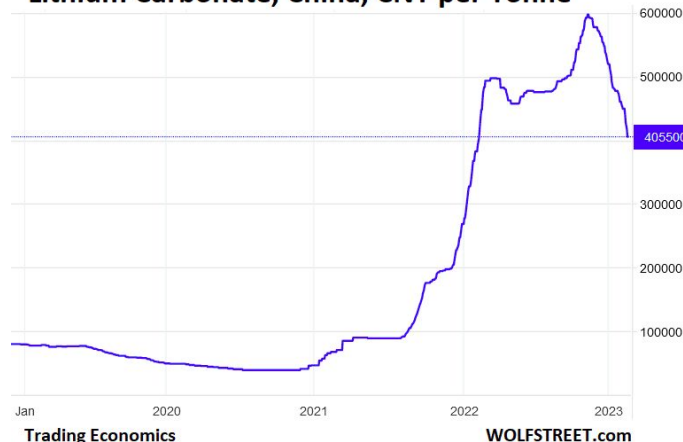
For comparison, the regular version of the Sehol E10X has two pack capacities, 19.7 kWh and 31.4 kWh, with a range of 200 km and 302 km, respectively. The higher capacity pack has an energy density of 141 Wh/kg.

The unveiling of the test vehicle means that sodium-ion batteries are starting to be used in passenger cars, after the new batteries were mainly used in electric two-wheelers and energy storage.

On July 29, 2021, [CATL](#) unveiled its first-generation sodium-ion battery, claiming that the single-unit energy density had reached 160 Wh/kg, the highest level in the world.

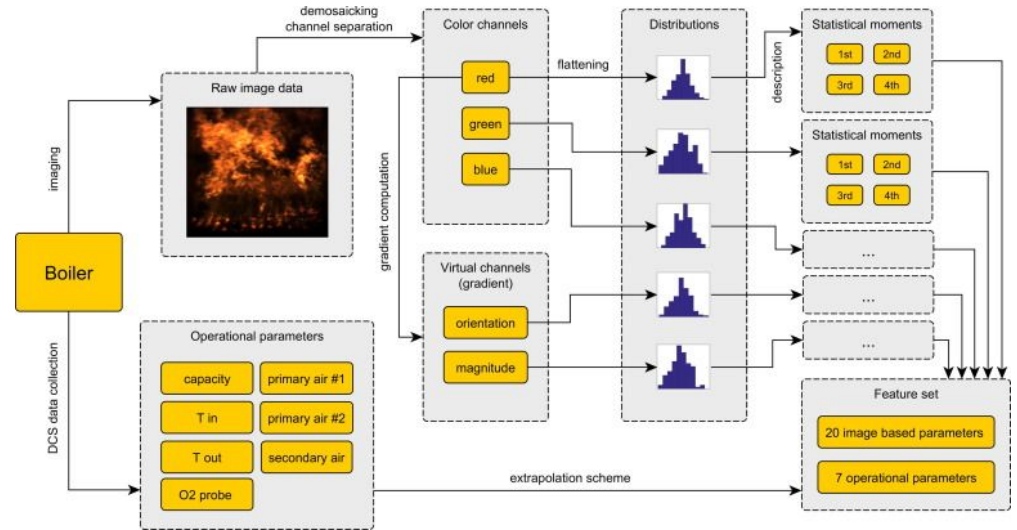
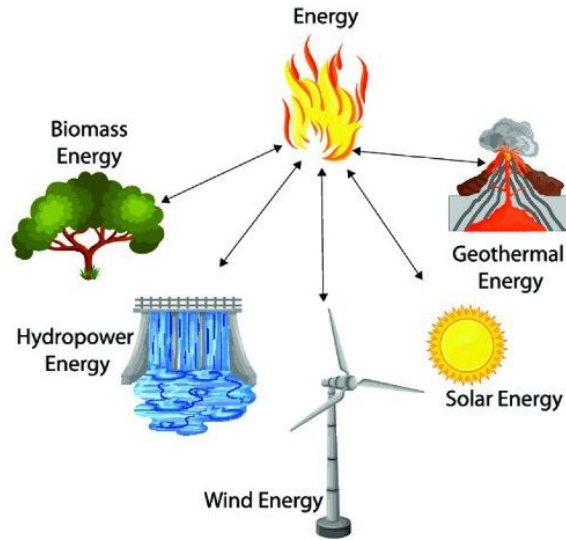
Overall, the energy density of the first-generation sodium ion battery is slightly lower than that of the current lithium iron phosphate battery. But it has clear advantages in low-temperature performance and fast charging, especially in high-power application scenarios in alpine regions, the company said at the time.

Lithium Carbonate, China, CNY per Tonne



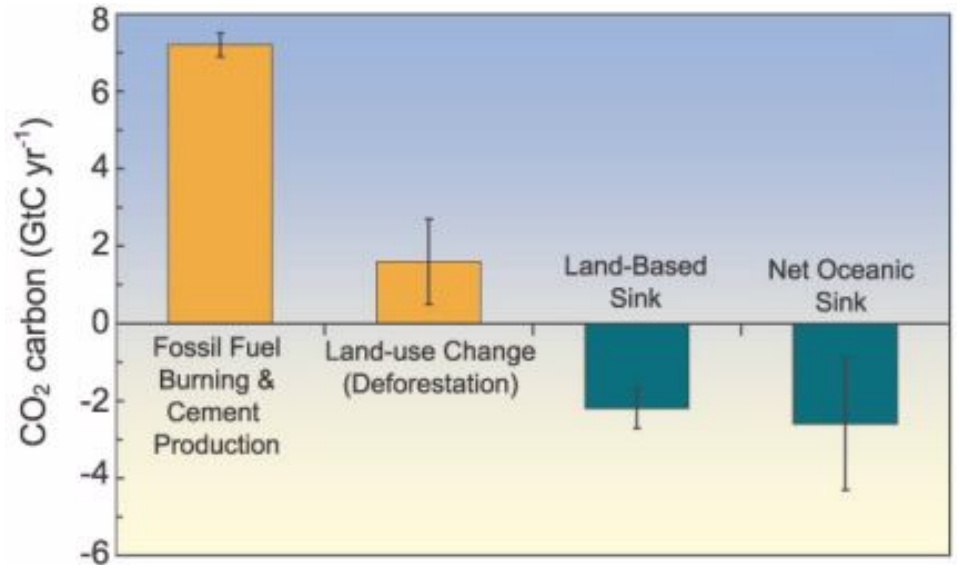
Recap

Renewable Energy



“Net zero”

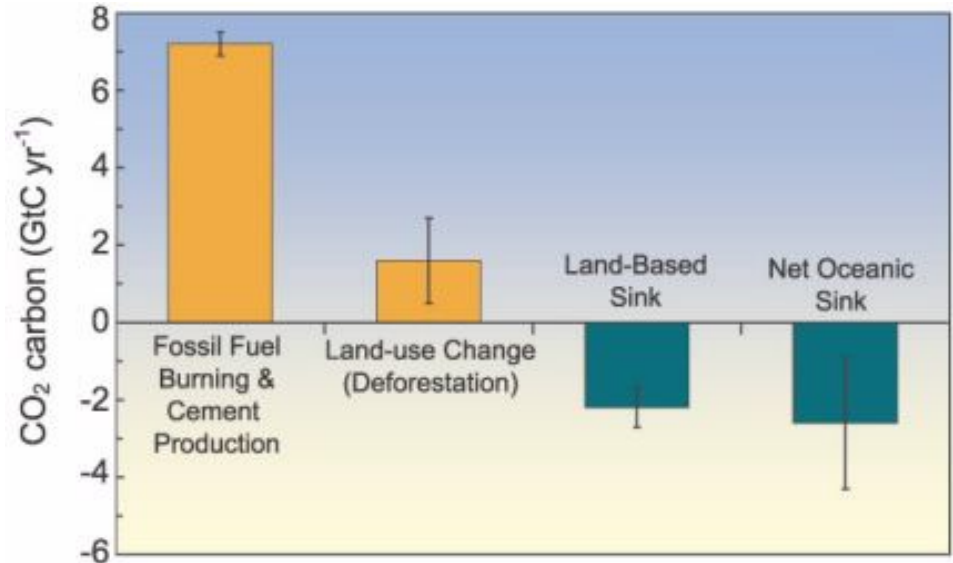
‘Net-zero emissions’ means that all sources of emissions are balanced out by the removal of GHGs.



“Net zero”

‘Net-zero emissions’ means that all sources of emissions are balanced out by the removal of GHGs.

Net *negative* emissions means that more GHGs are removed from the atmosphere than emitted



The IPCC on carbon dioxide removal

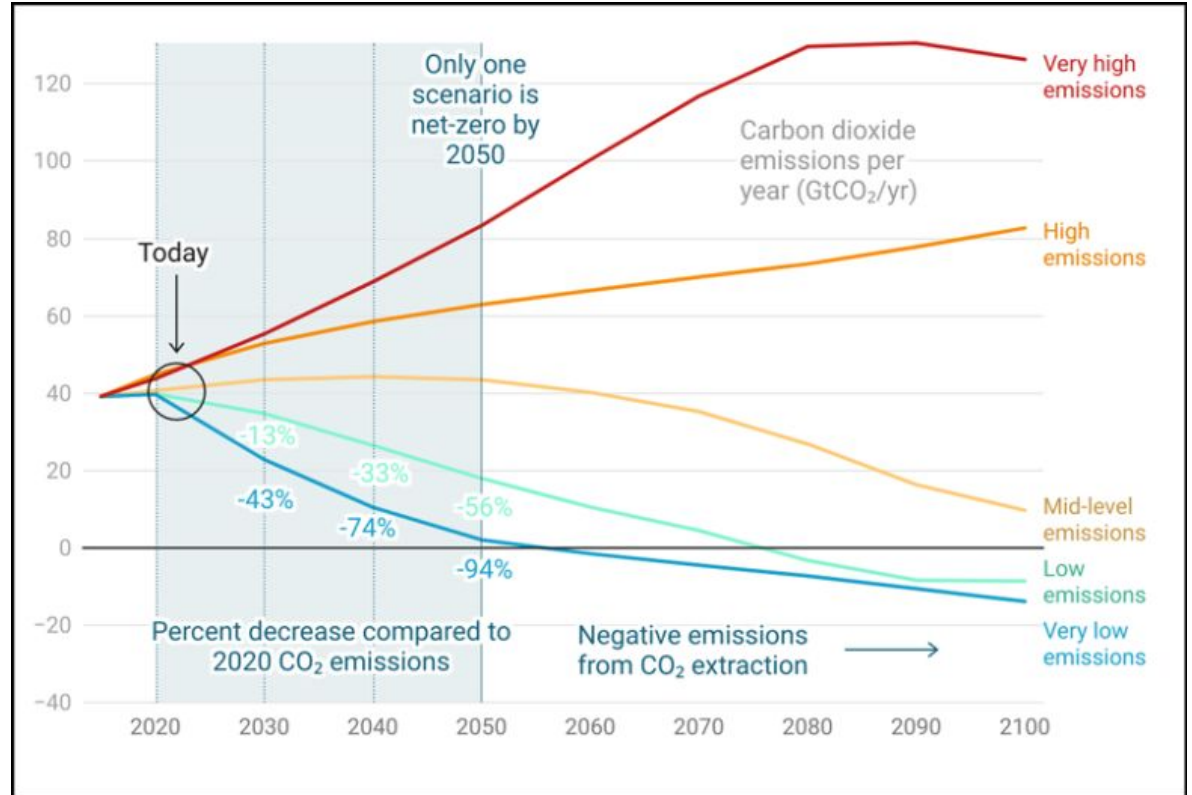
Methods for removing CO₂ from the atmosphere are “unavoidable” if the world is to reach net-zero – both globally and nationally, the report says.

It states with *high confidence* that net-zero can only be achieved if CO₂ removal is used to balance “difficult-to-abate” emissions from sectors that will find it harder to slash their climate impact, such as aviation, agriculture and some industrial processes.

In the longer term, upscaling CO₂ removal could provide “net-negative CO₂ emissions at the global level”, allowing a “reversal of global warming”, the report says with *medium confidence*.

Negative emissions

Most models of how we can now stay below 2 degrees C require net negative emissions at some point.

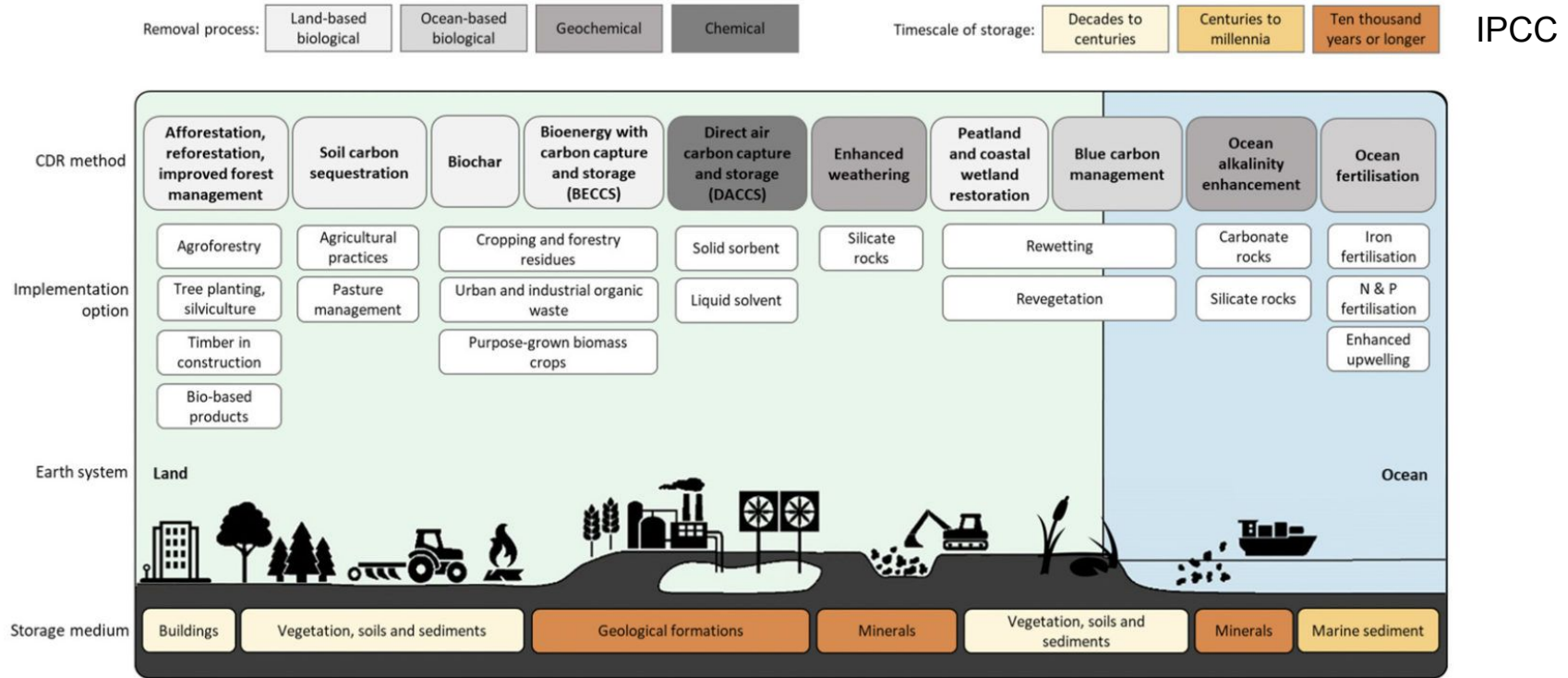


How can GHGs be removed from the atmosphere?

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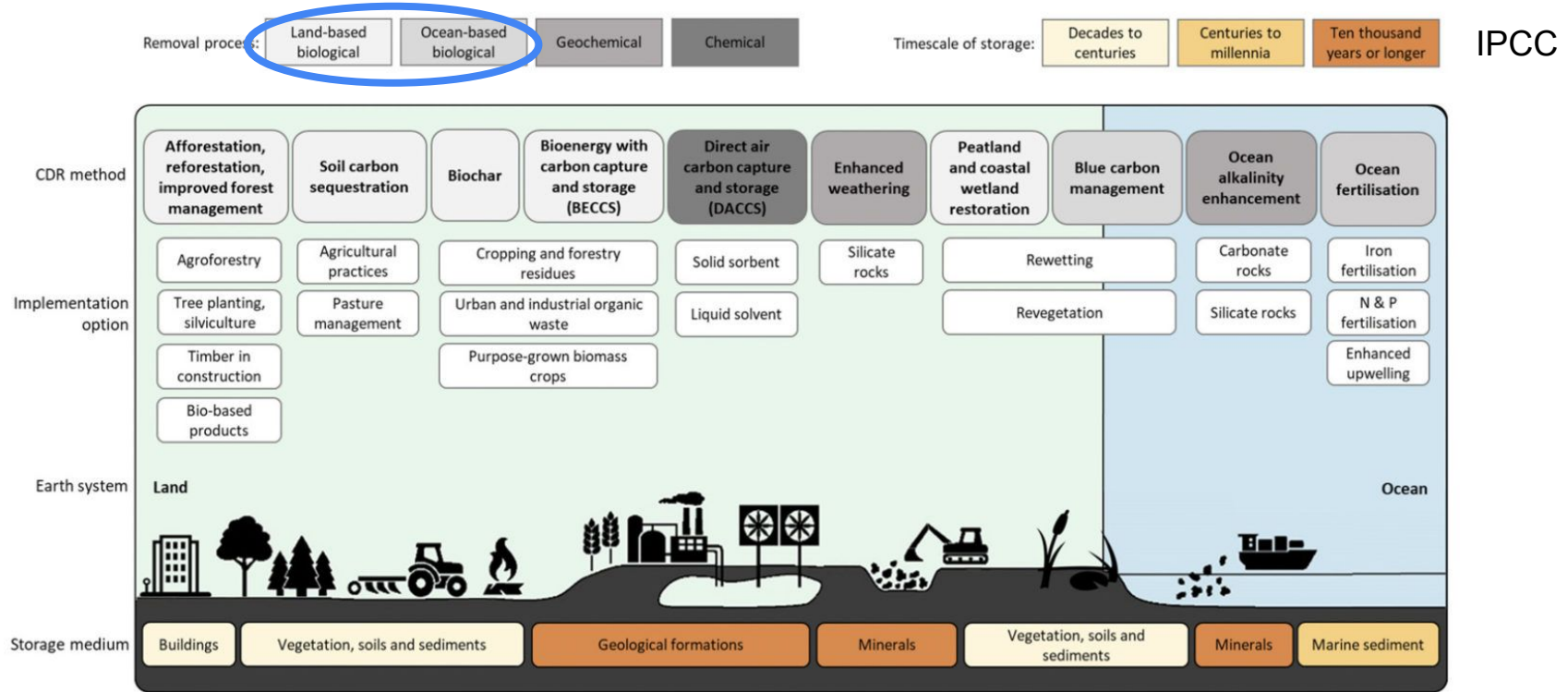
According to the IPCC, tree-planting and ecosystem restoration are the only “widely deployed” forms of CO₂ removal.

How can GHGs be removed from the atmosphere?



When evaluating removal methods, need to consider process (including energy) and permanence.

How can GHGs be removed from the atmosphere?



When evaluating removal methods, need to consider process (including energy) and permanence.

ML for ecological restoration

collaborative earth



Global Forests

Aron Boettcher ◉
University of Hawaii
Kyle Fisher ◉ Andre Otte ◉

We are building an accurate and global model for predicting potential rates of reforestation and resulting carbon sequestration. Such a model could have a transformational impact on global reforestation efforts by opening new streams of financing in the form of carbon credit futures.



Bison

Jason Baldes ◉ NWF & ITBC
Gisel Booman ◉ RegenNetwork
Emily Austin ◉ Colin Hill ◉
Valérie Lechêne ◉ Justin Lewis ◉
Jens Owen ◉ Jason Prasad ◉

Across the continent, a number of first nations are reintroducing bison to grasslands where they were once an ecologically vital species. Initial experiences and evolutionary considerations suggest that this may be ecologically beneficial in terms of biodiversity, carbon cycle, and resilience to climate change. However, these questions have not yet been studied at scale. In this lab, we will leverage remote sensing to scale up from ground measurements, establishing the large-scale patterns of bison impact.



Coastal Forested Wetlands

Elliott White Jr. ◉
Stanford University
Nikhil Raj Deep ◉ Aaron Hirsh ◉
Stephanie Kao ◉ Layla Tadjpour ◉

The goal of our lab is to create a high-spatial resolution map of coastal forested wetlands at global scale. If we know precisely where these ecologically critical but fragile forests are located, we can manage freshwater flows to counteract saltwater introgression due to rising sea levels, and we can assist in their migration inland, preserving their critical function in protecting coastlines and sequestering carbon.



Beaver

Grace Lindsay ◉
New York University
Avinash Mahech ◉ Cary Murray ◉
Chris Norcross ◉ Wendy Owens
Rios ◉ Quintin Tyree ◉

Beaver dams are known to result in greener, more drought-resilient waterways in semi-arid environments. We are using computer vision to spot dams in satellite imagery, generating a large dataset that we can use to train models that will tell us what the ecological effects of a dam will be at any point on a waterway. The goal is to create a tool to guide efficient restoration through the introduction of small dams.



Ganges

Anthony Acciavatti ◉
Yale University
Sarthak Arora ◉ Markley Boyer ◉
Nikhil Raj Deep ◉ Jiby Matthew
◉ James Smoot ◉ Michael

Warner ◉
In our pursuit of a successful and thriving relationship between humanity and natural systems, the Ganges river basin represents an extreme challenge. It is densely populated, remains agriculturally productive, and subject to an extremely powerful monsoon. We are mapping and analyzing a key feature of the Ganges basin—naalas—to understand how new forms of green infrastructure, such as parks, bioswales, and bioremediation, can rejuvenate this vital and sacred river.

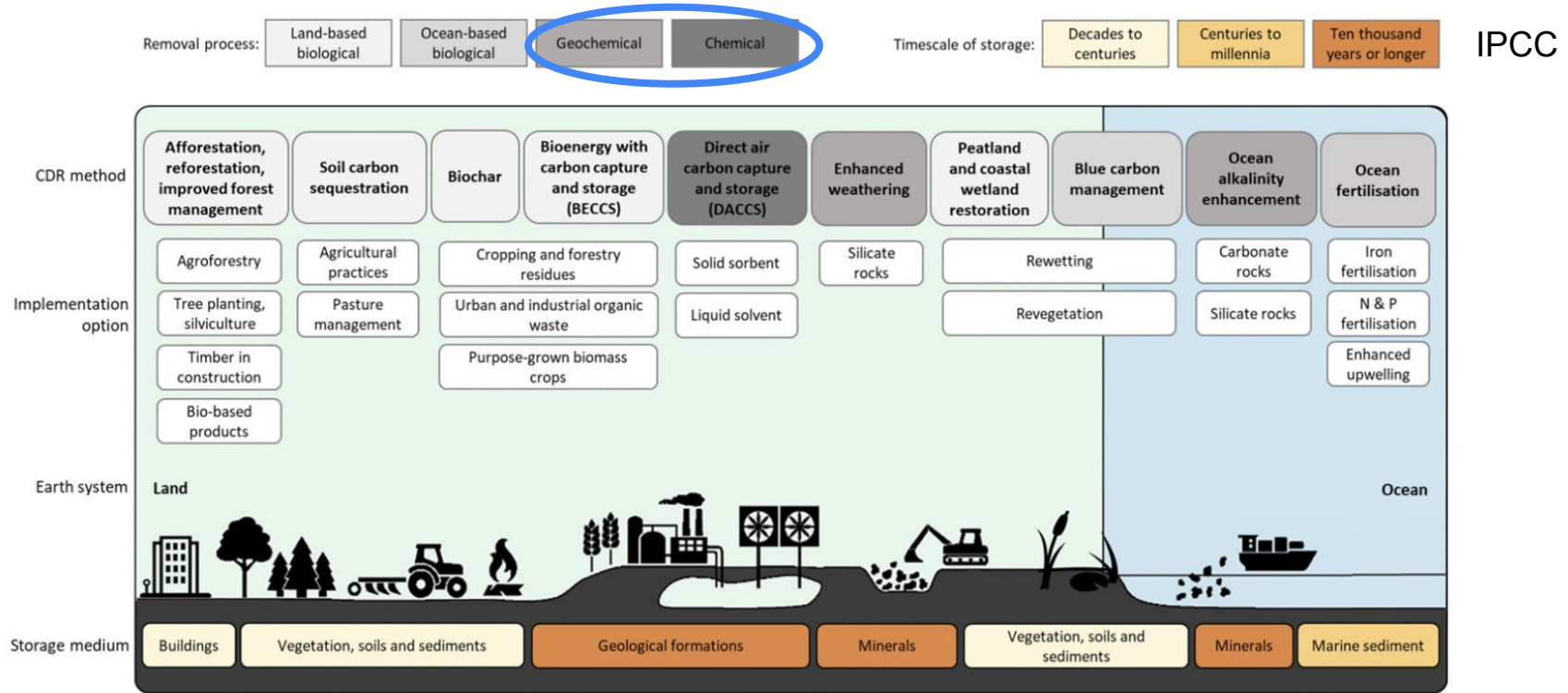


Assisted Forest Regeneration

Leland Werden ◉
ETH Zürich
Collaborative Earth AFR Data Team ◉

This project is pioneering the idea of a massively open literature review. We aim to quantify potential carbon capture and plant biodiversity recovery of forest, savannah, and mangrove assisted restoration projects. To do so, we are gathering and synthesizing unpublished data from field partners, integrating as much information from non-English sources as possible. There is a wealth of wisdom that has not been published in academic journals, and we aspire to integrate these insights into our review.

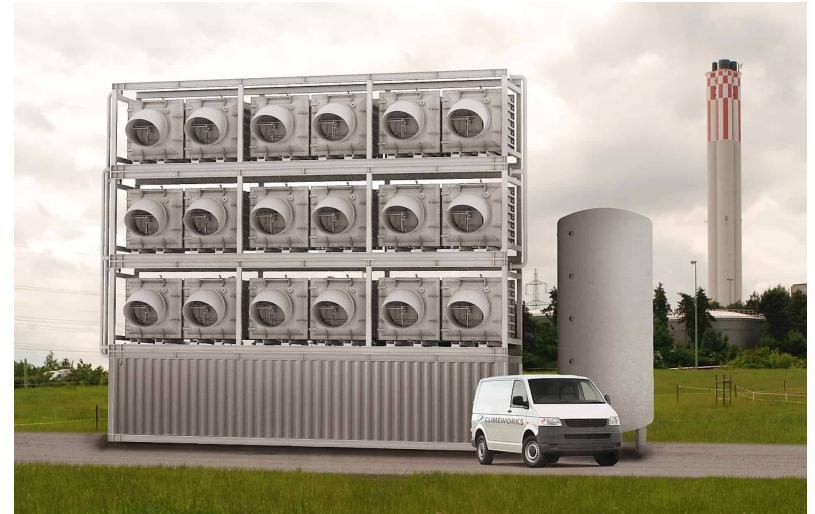
How can GHGs be removed from the atmosphere?



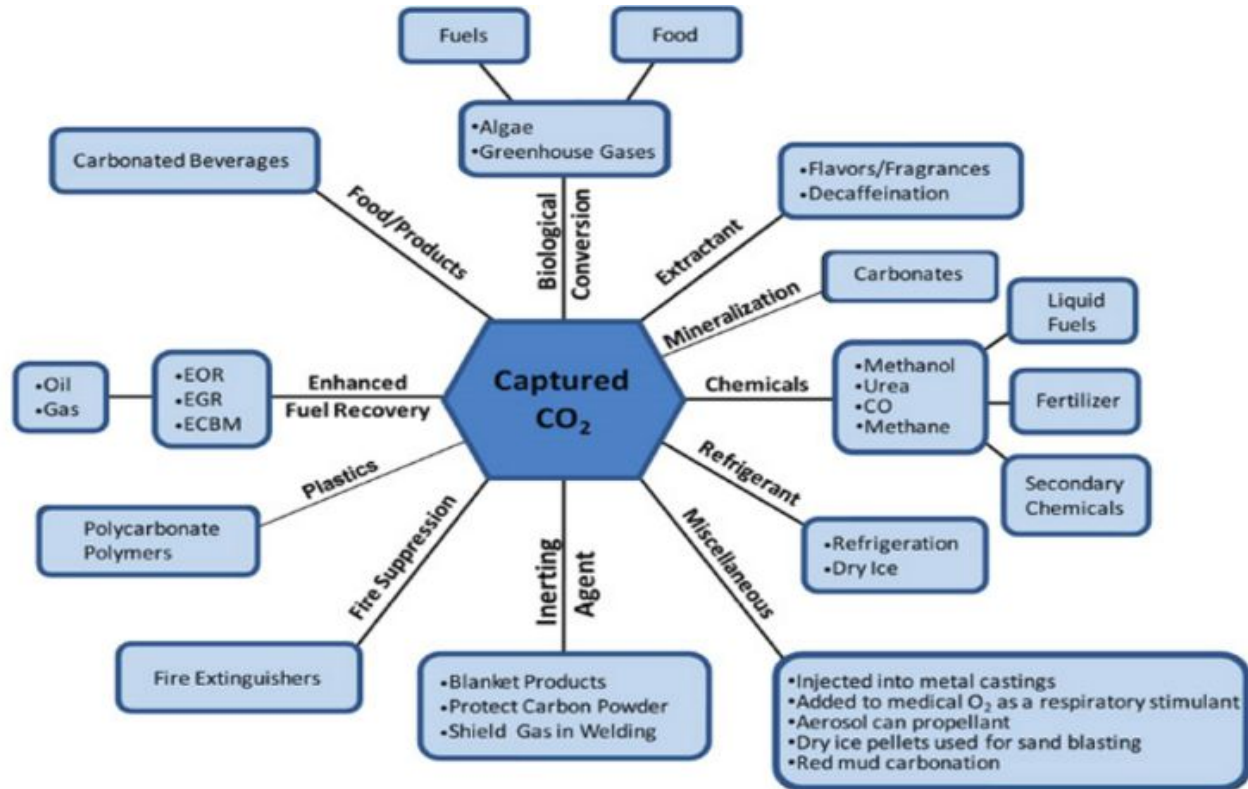
When evaluating removal methods, need to consider process (including energy) and permanence.

(Geo)chemical carbon dioxide removal

According to the IPCC: Despite limited use at present, technologies such as direct air capture, are projected to make a “moderate to large” contribution to future CO₂ removal



Uses of captured carbon



According to the IPCC...

The upscaling of CO₂ removal methods faces “various feasibility and sustainability constraints”

Direct air capture and storage is currently limited by its large energy requirements and by cost; the technology is at a “medium readiness level”.

Enhanced weathering, meanwhile, “has been demonstrated in the laboratory and in small scale field trials, but has yet to be demonstrated at scale”.

Paper deep dive



Chemical Engineering Journal

Volume 461, 1 April 2023, 141804



Surrogate modelling-assisted comparison of reactor schemes for carbon dioxide removal by enhanced weathering of minerals using seawater

Jinyuan Zhang^a, Aidong Yang^a  , Richard Darton^a, Lei Xing^b, Adam Vaughan^a

Show more 

Highlights

- CO₂ removal via enhanced weathering (EW) of minerals with seawater was studied.
- Two reactor models were extended to allow consistent comparison.
- Multi-objective optimization was efficiently assisted by surrogate modelling.
- Packed bubble column was shown to clearly outperform trickle-bed reactor.
- Forsterite weathering was more challenging than calcite for CO₂ removal.

Enhanced Weathering

A speed up of a natural process...



The need to optimize weathering reactors

Recent studies have developed mathematical models to evaluate the reactors, following early explorations of mineral weathering in engineered devices.

Such reactors offer an enclosed space and controlled conditions to enhance weathering rates, compared to implementation in open environments.

However initial modelling results predicted significant energy and water demand, ***suggesting the need to optimise selection and design of reactor schemes as important steps for further assessing their potential.***

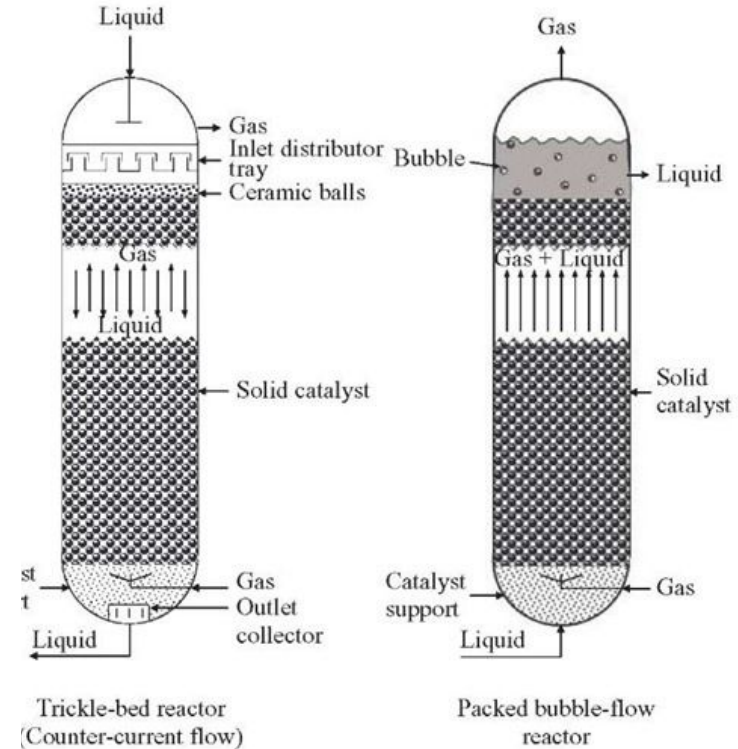
Two reactor types

Trickle-bed reactor (TBR): Liquid travels through gas

Packed bubble column (PBC): Gas travels through liquid

In both cases, gaseous CO₂ and solid materials dissolve into the liquid and then react with each other to form bicarbonate.

In this study they use salt water reactors, so that water supply isn't an issue.



Problem: reactors need a lot of energy and space

To capture 1 tonne of CO₂ (~per person emissions for one-way transatlantic flight), a mattress-sized reactor can consume electricity equivalent to the monthly electricity of a household.

Increasing the CO₂ removal rate of the reactor reduces the space it needs but almost always increases the amount of energy it needs.

What are the controllable settings of the reactors?

Amount of removed carbon can depend on the concentration of CO₂ in the incoming air, the speed of gas and liquid through the reactors, and the properties of the solids.

Changing these variables will also change the amount of energy used.

Table 1. Decision variables and their ranges.

Decision variables	Unit
Reactor feed CO ₂ concentration (mol fraction) ($x_{\text{CO}_2,0}$)	–
Flow parameter (F_{lv})	–
Operating parameter (OP)	–
Superficial gas velocity (u_{G})	m s ⁻¹
Liquid to gas superficial velocity ratio	–
Solid bed height (H_{bed})	m
Initial particle radius, for calcite ($r_{\text{p}0}$)	m

Goal

Find a parameter setting of the reactor that optimizes the tradeoff between energy and space, and compare the optimized states across reactor types.

Brainstorm

What kind of data would you want to have to be able to approach this problem?

What kind of methods would you apply?

How would you measure success?

What difficulties may you face?

“Data”

Difficult to get a lot of data from these reactors in the real world.

But these systems represent decently well-understood physical and chemical processes, therefore...

“Data”

downward movement of particles. Adopting an approach similar to that previously used to model solid biomass changes in an evolving biofilm [18], [19], a conservation equation for the particle surface area per unit bed volume, denoted by a_s (m^{-1}), is used:

$$\frac{\partial a_s}{\partial t} + \frac{\partial(va_s)}{\partial x} = R_a \quad (3)$$

$$a_s|_{x=0} = a_{s0} \quad (4)$$

where t (s) is time, x (m) is the (axial) spatial co-ordinate, v (m s^{-1}) is the advective velocity of the bed due to particle dissolution, and a_{s0} (m^{-1}) is the specific surface area at the (top) feeding layer of the bed, determined by the size of the feed particles and bed porosity (see equations (7), (8)). R_a ($\text{m}^{-1} \text{s}^{-1}$) denotes the rate of reduction of a_s due to dissolution and can be calculated as follows (for derivation, see [Supplementary Material](#), Section S1):

$$R_a = -12(1 - \epsilon)d_p^{-2}\rho_p^{-1}M_pR_d \quad (5)$$

where ϵ is the bed porosity and remains approximately constant (~ 0.39) for the range of particle size and bed diameter considered in this work, d_p is the particle diameter, M_p (kg mol^{-1}) is the molecular weight of the particles, ρ_p (kg m^{-3}) is the particle density, and R_d ($\text{mol m}^{-2} \text{s}^{-1}$) is the specific surface dissolution rate, determined by the dissolution kinetics incorporated in the existing weathering reactor models [3], [4].

The advective velocity v is modelled as below:

$$\frac{\partial v}{\partial x} = -\frac{R_m}{\rho_p} \quad (6)$$

$$v|_{x=H_{bed}} = 0 \quad (7)$$

where R_m ($\text{kg m}^{-3} \text{s}^{-1}$) is the mass rate of particle dissolution (per unit particle volume) and is calculated from R_d :

$$R_m = R_d a_p M_p \quad (8)$$

a_p (m^{-1}) is the specific surface area per unit volume of particle, related to a_s and particle diameter d_p (m) by:

2.2.4. Modelling kinetics of forsterite dissolution

Forsterite dissolution is considered to follow the chemical reaction below:



The specific surface dissolution rate R_d is modelled by adopting a previously proposed kinetics equation [20] to account for the effect of saturation:

$$R_d = \left[A_1 e^{\frac{-E_1}{RT}} (a_{H^+})^n + A_2 e^{\frac{-E_2}{RT}} \right] \left(1 - \frac{Q}{K_{eq}} \right) \quad (12)$$

where A_1 (A_2) ($\text{mol m}^{-2} \text{s}^{-1}$) is the pre-exponential Arrhenius constant and E_1 (E_2) (kJ mol^{-1}) is activation energy to account for the dissolution with (without) the impact of pH. T (K) is temperature, R ($\text{kJ mol}^{-1} \text{K}^{-1}$) is the gas constant, a_{H^+} (mol L^{-1}) is the activity of hydrogen ions, n is the reaction order for hydrogen ions, Q (L mol^{-1}) is reaction activity coefficient and K_{eq} (L mol^{-1}) is the equilibrium constant of dissolution.

The reaction activity quotient is given by:

$$Q = \frac{a_{H_4SiO_4} (a_{Mg^{2+}})^2}{(a_{H^+})^4} \quad (13)$$

The temperature-dependent equilibrium constant, K_{eq} , is given by the following correlation:

$$\log_{10} K_{eq}(T) = A + BT + \frac{C}{T} + D \log_{10} T + \frac{E}{T^2} \quad (14)$$

where the constants were obtained from the Thermoddem geochemical database [26].

Further details of the calculation of activity coefficients and the parameter values adopted for equations (10), (12) are provided in [Supplementary Material](#) (Section S2).

“Data”

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$$R_a = -12(1 - \epsilon) d_p^{-2} \rho_p$$

where ϵ is the bed porosity and remains approximately constant (~ 0.39) for the range of particle size and bed diameter considered in this work, d_p is the particle diameter, M_p (kg mol^{-1}) is the molecular weight of the particles, ρ_p (kg m^{-3}) is the particle density, and R_d ($\text{mol m}^{-2} \text{s}^{-1}$) is the specific surface dissolution rate, determined by the dissolution kinetics incorporated in the existing weathering reactor models [3], [4].

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Use equations to determine what the different reactors need in order to remove 1 ton of CO2 using different reactor settings

E_1 (E_2) (kJ mol $^{-1}$) is the activation energy of the reaction, n is the reaction order with respect to a_{H^+} , Q is the reaction activity quotient, K_{eq} (L mol $^{-1}$) is the equilibrium constant of dissolution.

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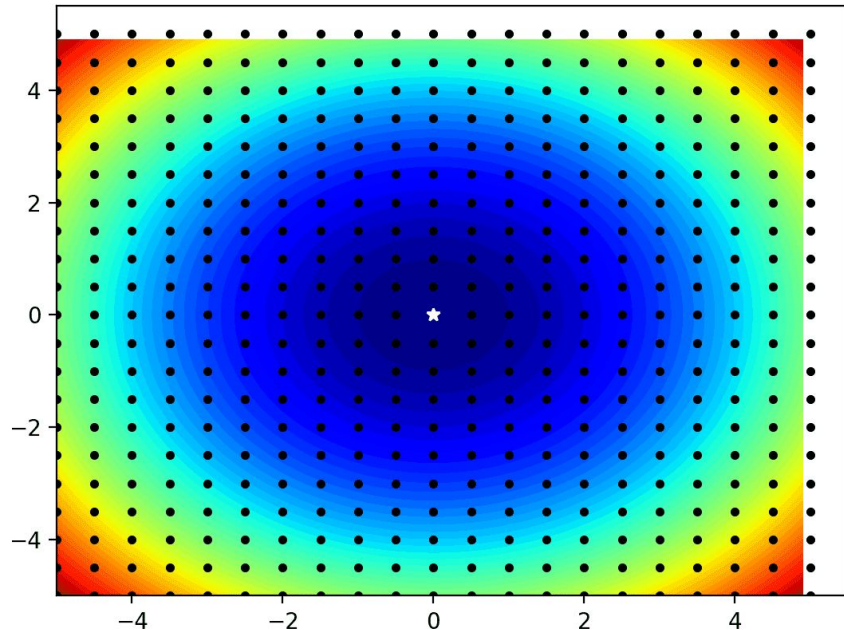
Further details of the calculation of activity coefficients and the parameter values adopted for equations (10), (12) are provided in [Supplementary Material](#) (Section S2).

How can the optimal reactor settings be found?

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One option: brute force.

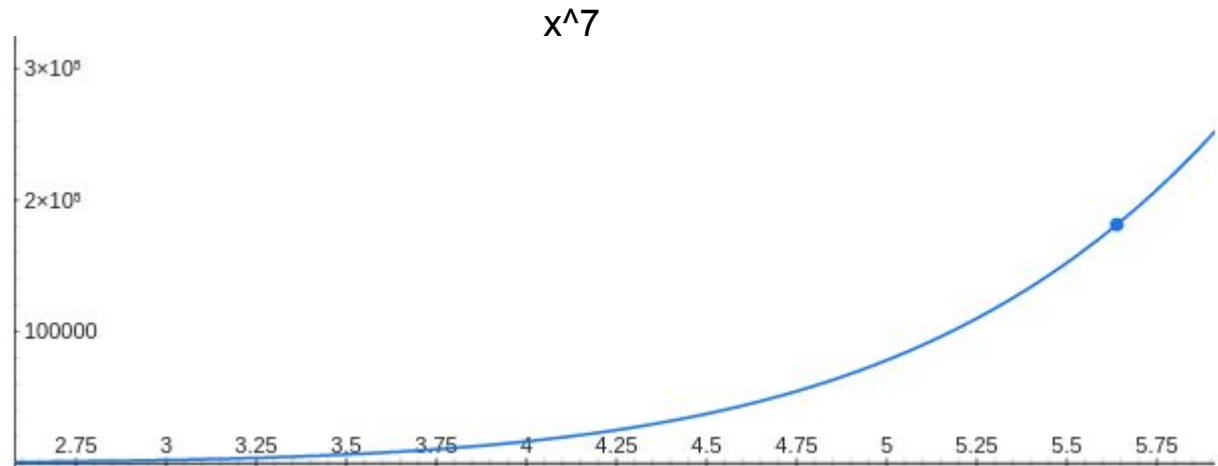
Run the equations for a large selection of reactor settings and observe the energy and space needs.



How can the optimal reactor settings be found?

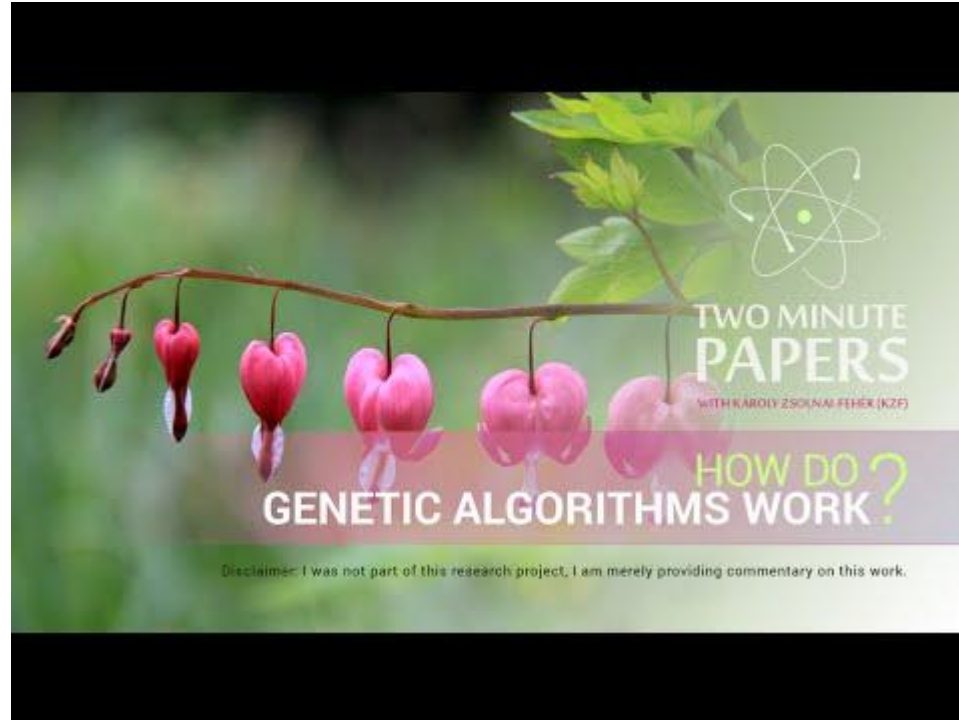
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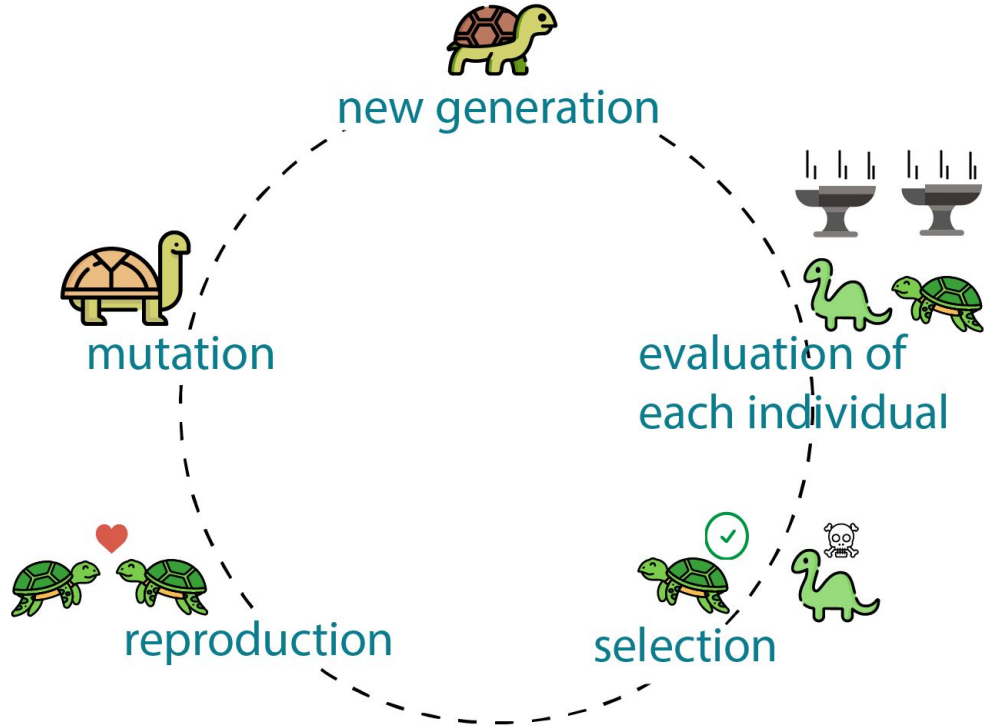
Genetic algorithms



How can the optimal reactor settings be found?

Genetic algorithms.

What is the “selection”
process here?



Objective function

2.3.1. Formulation of the optimisation problem

Each reactor is optimised by considering the minimisation of two competing objective functions, namely the specific energy consumption, *SEC*, in GJ tonne^{-1} and the specific space requirement, *SAR*, in $\text{m}^2 (\text{tonne yr}^{-1})^{-1}$, where “tonne” refers to CO_2 removal. In this study, every reactor simulation run was for the continuous operation of 1 year starting from a bed filled with particles at their initial size, and the *SEC* and *SAR* used in optimisation were average values over the year. A weighted sum method is adopted to combine the two objectives:

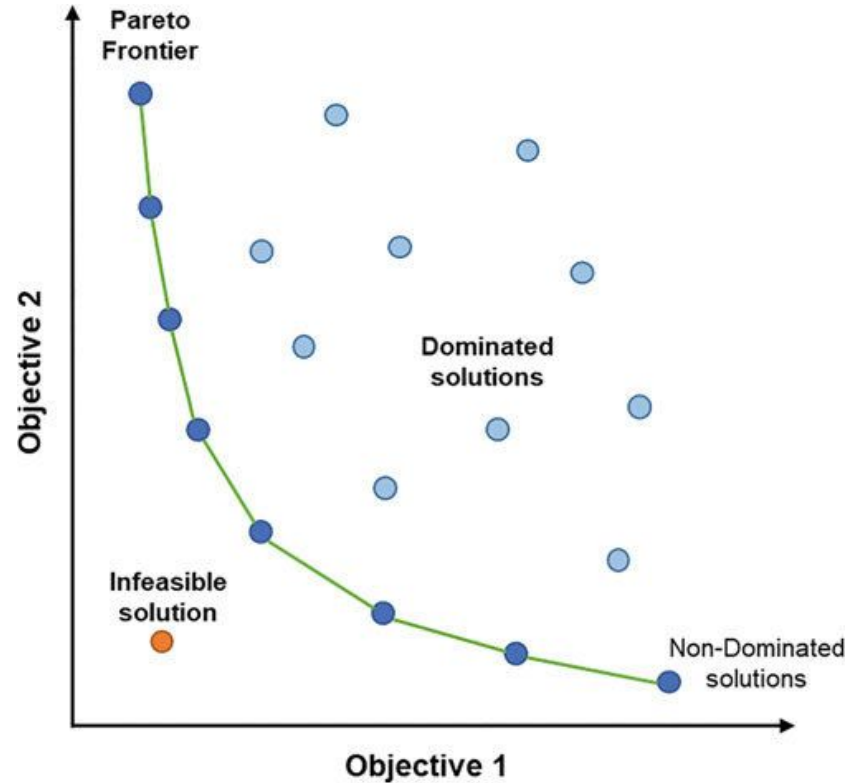
$$\text{Minimise } y = w \cdot \text{SEC} + (1 - w) \cdot \text{SAR} \quad (15)$$

What happens as we vary w from 0 to 1?

Objective function

Pareto front

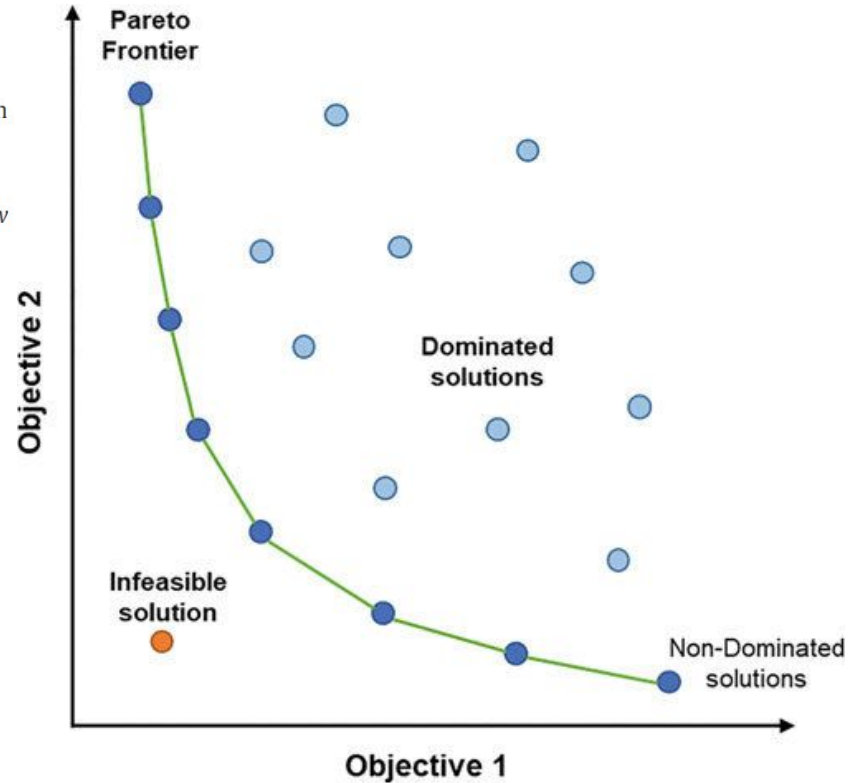
(based on idea of pareto optimality from game theory: where no action or allocation is available that makes one individual better off without making another worse off)



Objective function

During the computational procedure, the weighting factor w increases from 0 to 1 by an increment (set to be 0.05). At each value of w , the optimisation problem is solved to produce one solution point; all the solution points collectively form the Pareto front curve as the overall result of the two-objective optimisation. The chosen increment in w proved to be able to yield Pareto front curves with adequate shapes (see Fig. 4, Fig. 5).

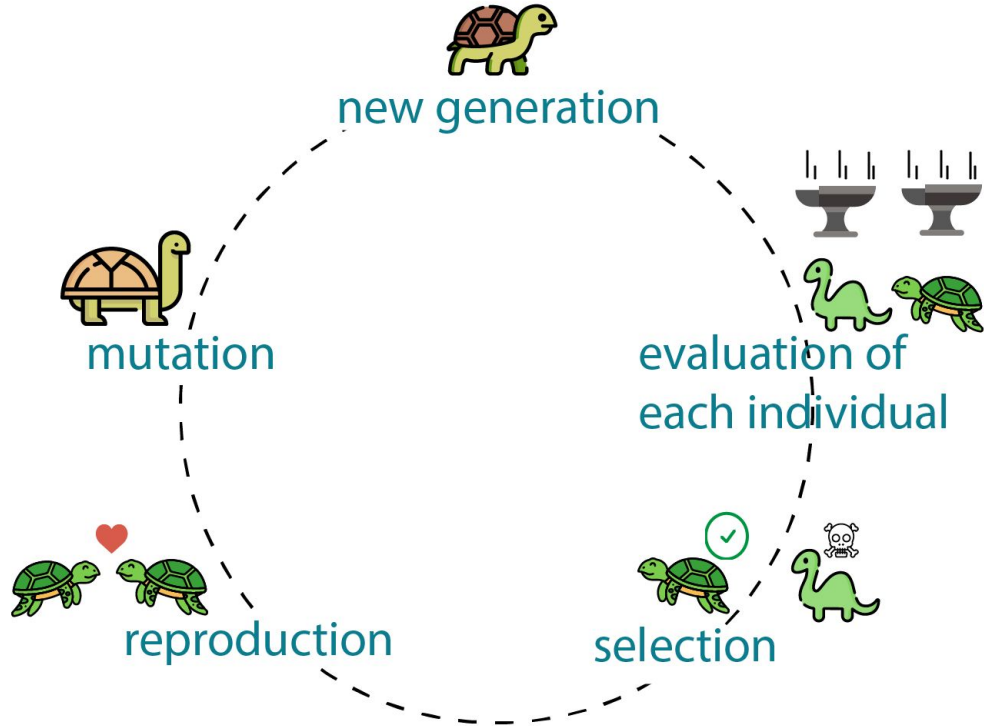
$$\text{Minimise } y = w \cdot \text{SEC} + (1 - w) \cdot \text{SAR}$$



How can the optimal reactor settings be found?

Genetic algorithms still require evaluating a large amount of models.

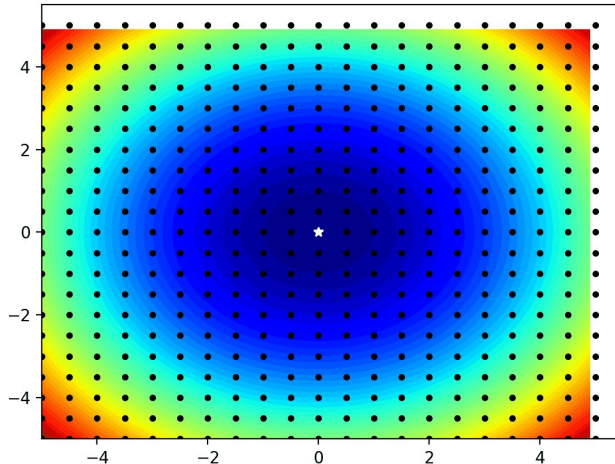
What can we do if we don't want to have to run the full set of equations each time?



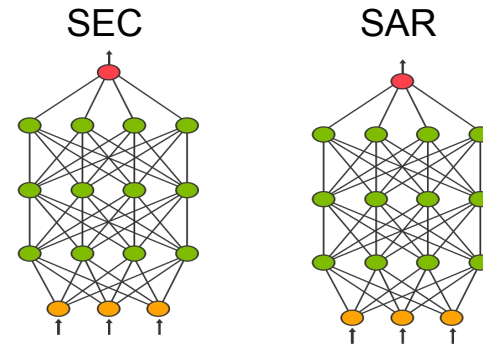
Surrogate models!

Train an artificial neural network to replicate what the full set of physical equations does.

Get a data set for training by running the equations on a small set of reactor settings:



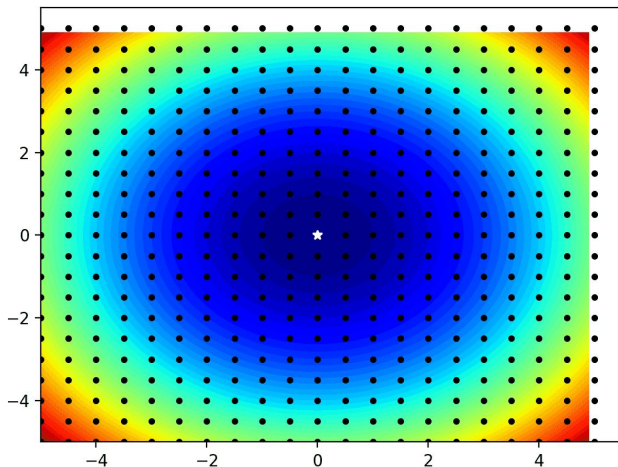
Train networks that map reactor settings to energy and space outputs:



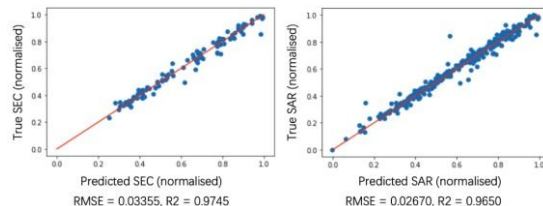
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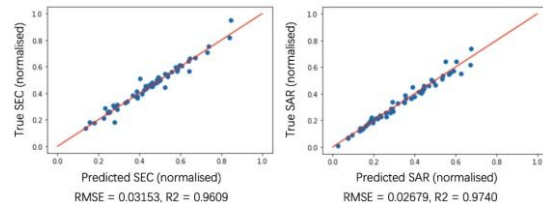
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Train networks that map reactor settings to energy and space outputs:



(a) TBR-calcite



(b) PBC-calcite

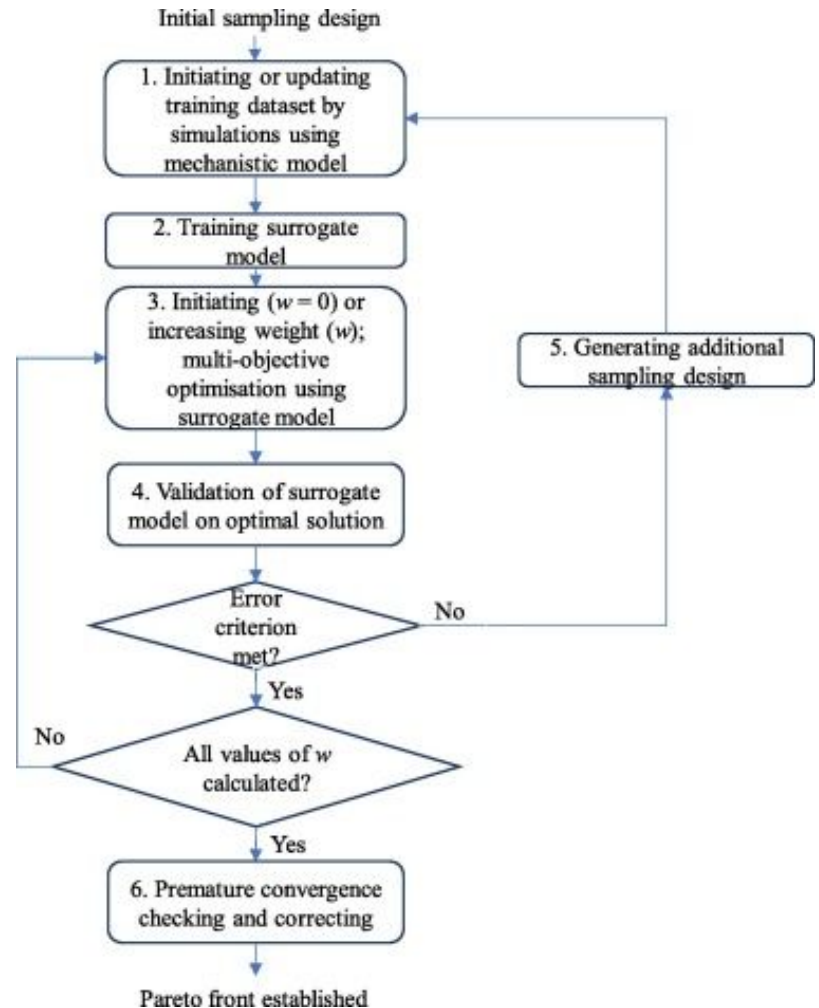
Overall procedure

Run the physical equations to get training data.

Train the ANNs.

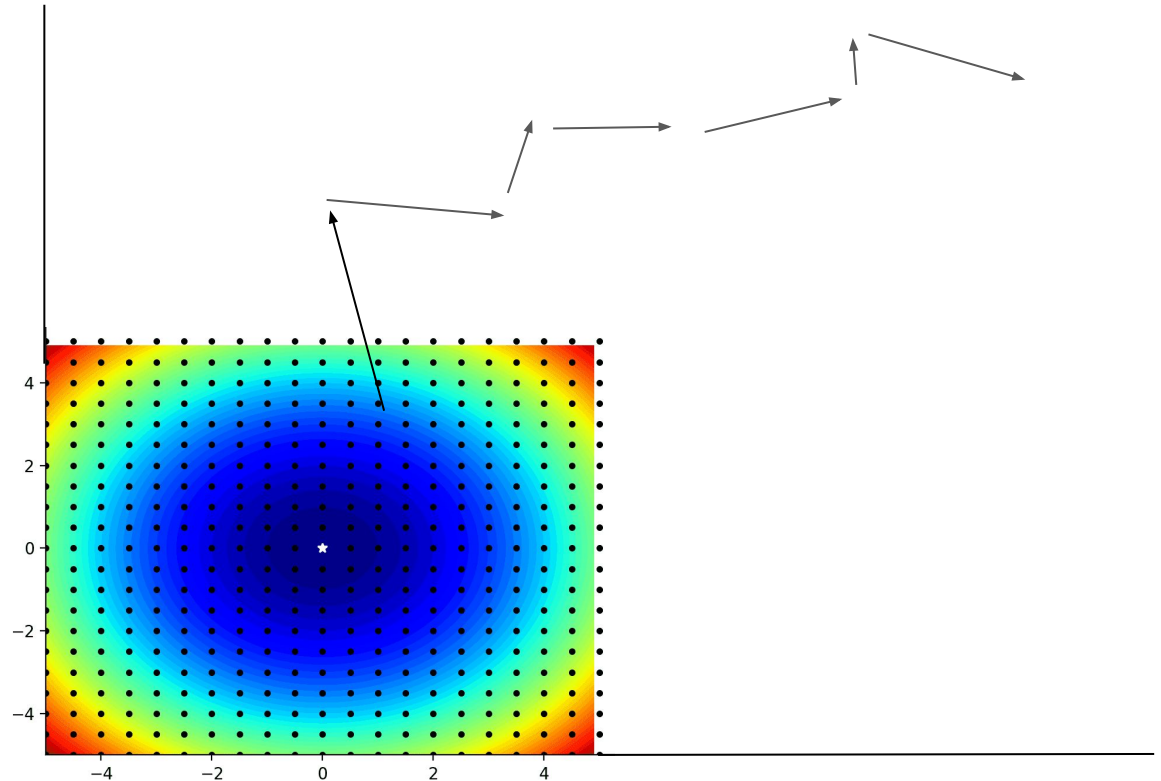
Run the genetic algorithm using a given w value and the ANNs as surrogate models.

Run the physical equations using the optimal value found by the GA. ***Was the ANN prediction actually correct?***

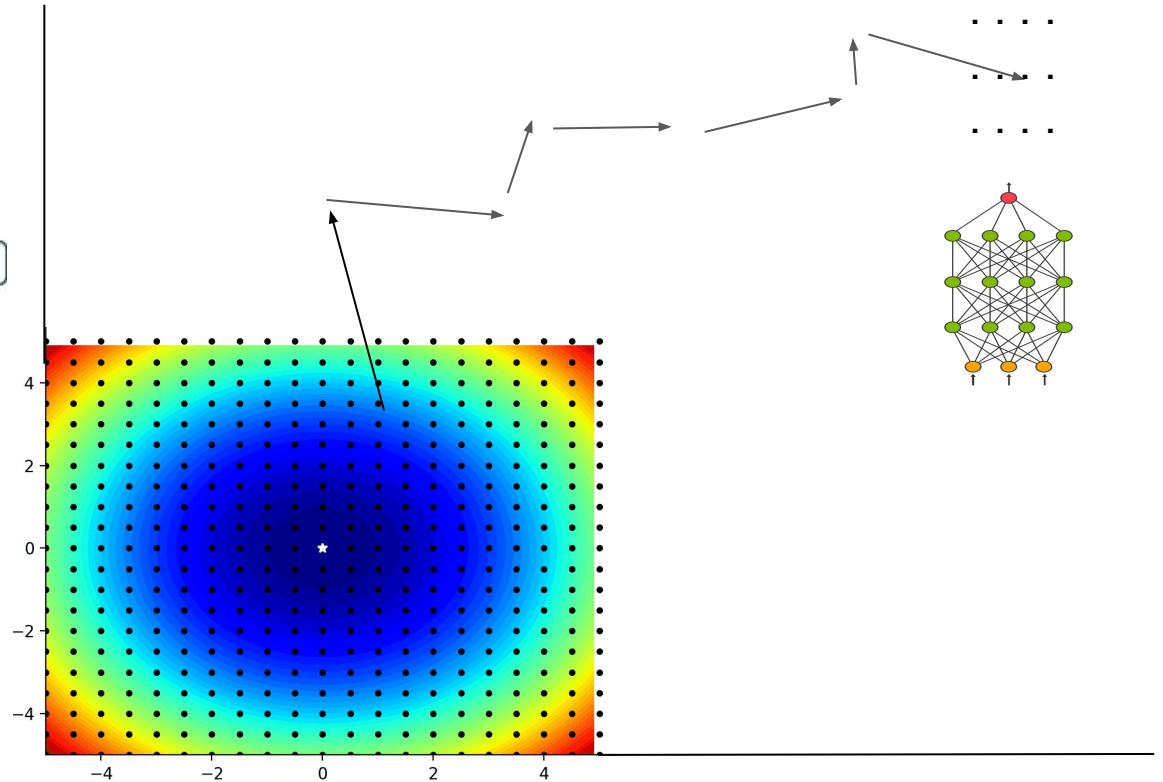
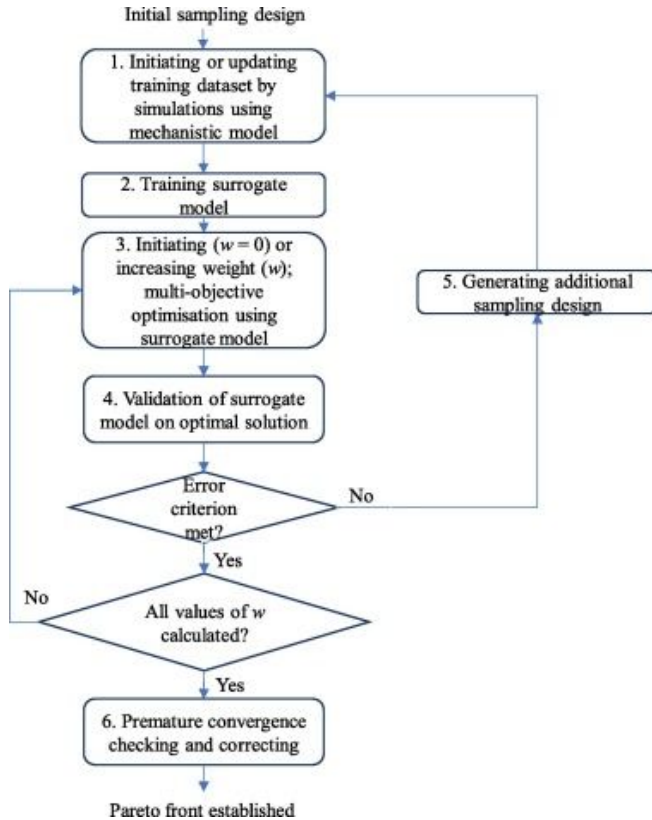


Validating/re-training ANNs on a different parameter space

The genetic algorithm can explore reactor settings that the ANN was not trained on. If it strays too far, the ANN might not be an accurate model anymore and need to be re-trained.



Validating/re-training ANNs on a different parameter space



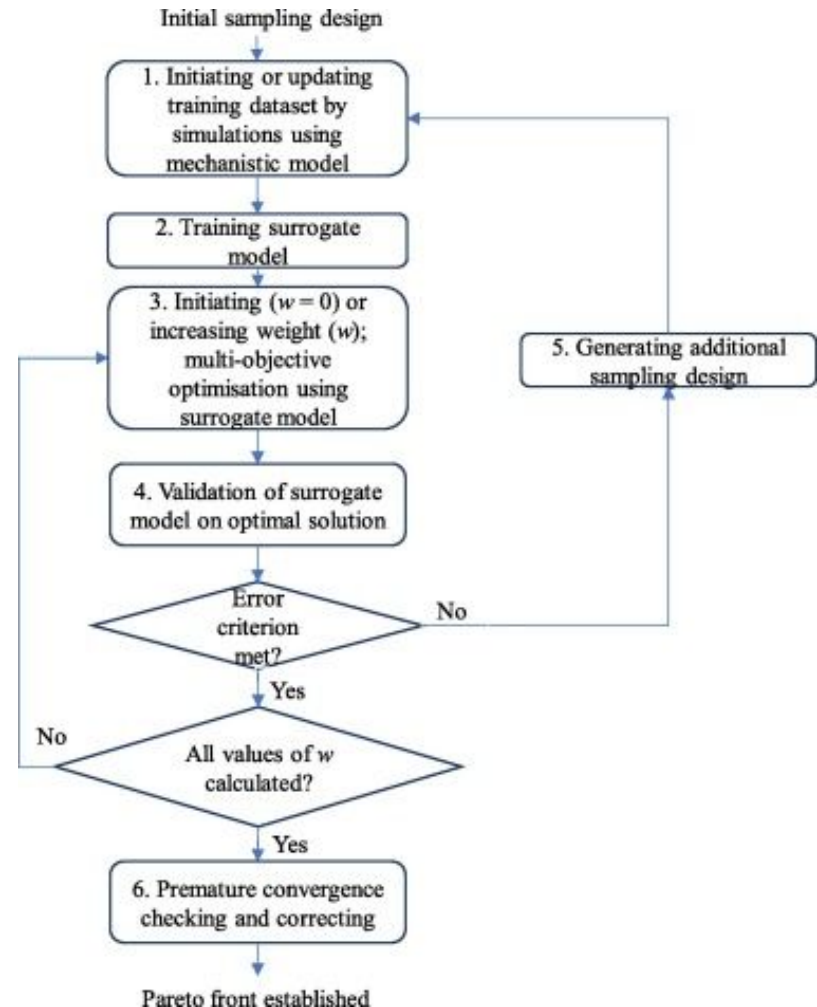
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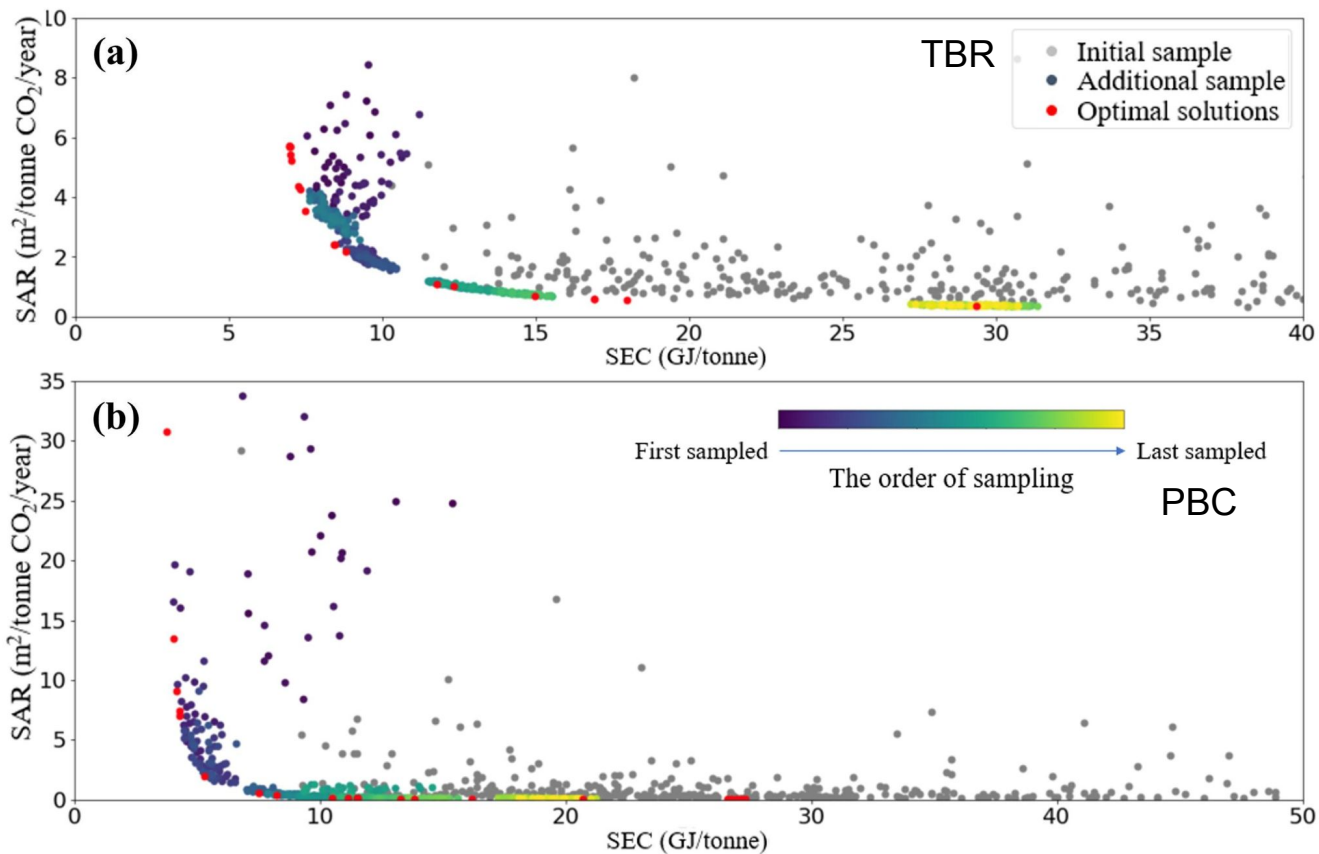
Run the genetic algorithm using a given w value and the ANNs as surrogate models.

Run the physical equations using the optimal value found by the GA. ***Was the ANN prediction actually correct? Then move on to next value of w***



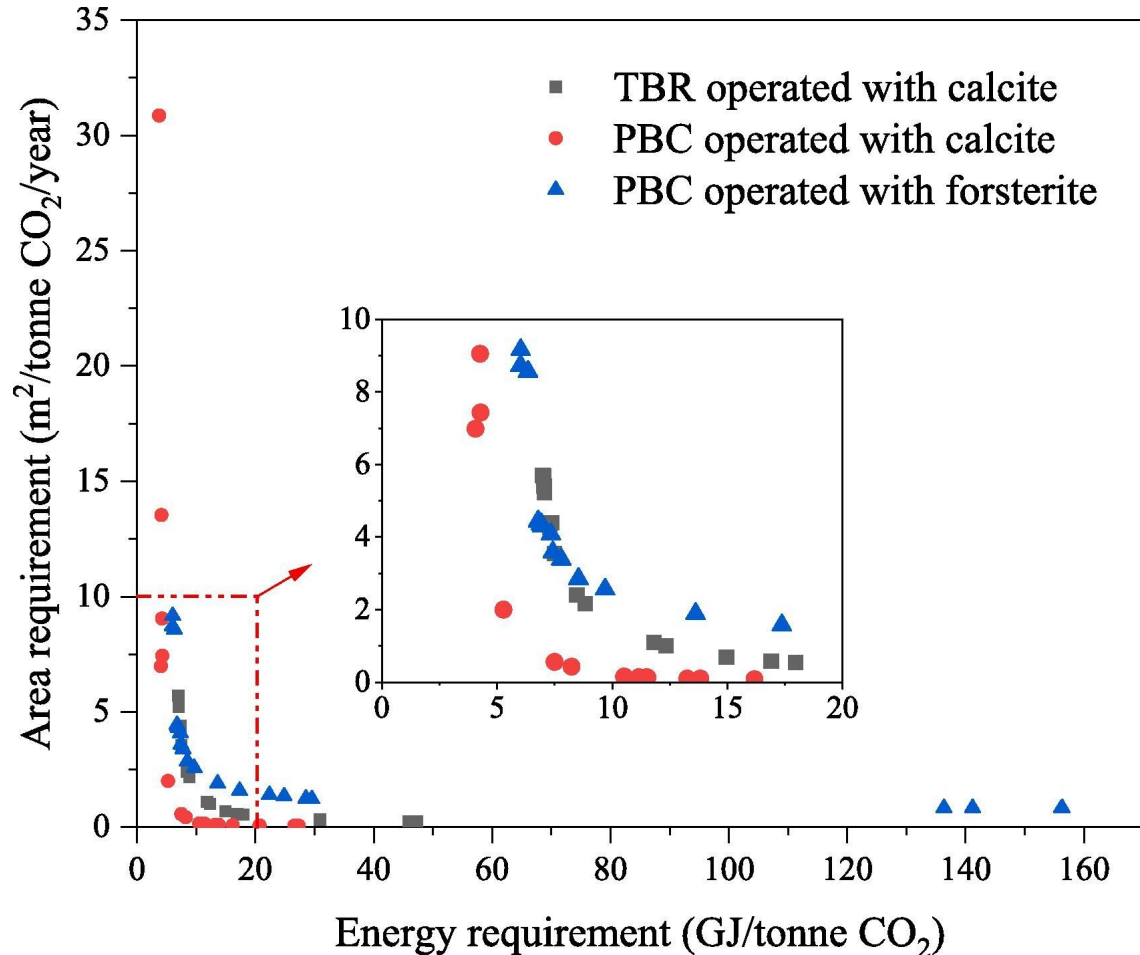
Results

Solutions found
change as w
changes



Results

This method can be used to compare reactors and materials. Here it finds that the PBC reactor with calcite can remove 1 ton of CO₂ for the least space and energy.



Conclusions

“Combined with the development and application of a robust computational procedure for surrogate model-based multi-objective optimisation, these two reactor types have been rigorously compared considering different trade-off positions of two competing objectives, energy consumption and space (area) requirement. ***With the weathering of calcite, the PBC has been clearly shown to be more efficient than the TBR***, thanks to its better mass transfer performance, with the optimal trade-off solution predicting an energy consumption of 5.29 GJ tonne⁻¹ CO₂ at a modest space requirement.

Overall, this work has clearly identified the advantage of the PBC over the TBR in mass transfer, and quantified the challenges associated with the use of slow-dissolving minerals for enhanced weathering. ***We expect that the modelling approaches and learning from this work will inform future exploration of reactor designs***, together with the further investigation of devices for CO₂ enrichment, to reliably establish the true potential of reactor-based enhanced weathering for atmospheric CO₂ removal.”

Further resources

Air Miners

<https://airminers.org>

WHERE ARE YOU IN YOUR CARBON REMOVAL JOURNEY?

I'M STARTING A CARBON REMOVAL COMPANY

Launchpad is an accelerator program for founders of early stage carbon removal companies looking to rapidly gain traction for their business goals.

ACCELERATE YOUR STARTUP

I WANT TO NETWORK WITH FELLOW INNOVATORS

A community to call home for those who want to contribute and develop ideas in carbon removal with 1,600 other like minded individuals.

FIND YOUR PEOPLE

I'M NEW TO THE FIELD AND WANT TO LEARN MORE

A 5-week group learning crash course for people who are new to carbon removal and want to make a difference in the world.

START YOUR JOURNEY

Summary

