

Dynamic Bias and Estimates of Climate Impacts on Growth

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May 2025

Motivation

- Researchers study the impact of climate change on many outcomes.
 - Economics growth (GDP) [Dell et al., 2012].
 - Crop yields [Annan and Schlenker, 2015] [Burke et al., 2015].
- Measuring these impacts helps policymakers adapt effectively.
- Researchers create models using panel data.
 - Data from multiple units (i) over time (t).
- Commonly used statistical models ignore **dynamics**.
 - Leads to inaccurate estimates. Leads to "dynamic bias" (this paper). I fix with new estimator with bias correction.

Motivation

- Traditional models ignore that outcomes are dynamic, influenced by past outcomes.

$$\text{GDP}_{i,t-1} \rightarrow \text{GDP}_{i,t}. \quad (1)$$

- Past GDP influences future GDP through investment [Solow, 1956].
- Past yields influence future yields through agricultural practice and market [Griliches, 1963].
- Ignoring dynamics in model leads to incorrect estimates of climate impacts.
 - Example, changes effect of temperature on hotter years on GDP growth by 10% and GDP levels by 120%.

Traditional Methods

- Static models are commonly used to estimate the effects of climate shocks.
[Jessee et al., 2018] [Dell et al., 2012] [Cho, 2017] [Graff Zivin et al., 2018]
[Garg et al., 2020][Annan and Schlenker, 2015] [Burke et al., 2015]
[Drabo and Mbaye, 2015] [Mahajan and Yang, 2020] [Missirian and Schlenker, 2017].

$$\text{Static Model : } \text{GDP}_{i,t} = \alpha_i \text{country}_i + \beta_2 \text{temperature}_{i,t} + \epsilon_{i,t} \quad (2)$$

- Dynamics ignored because $\text{GDP}_{i,t-1}$ is omitted.
- This leads to bias in treatment effect coefficients ($\hat{\beta}_2$).
 - This bias occurs even if the climate shock (temperature) is randomly assigned!

Alternative Method

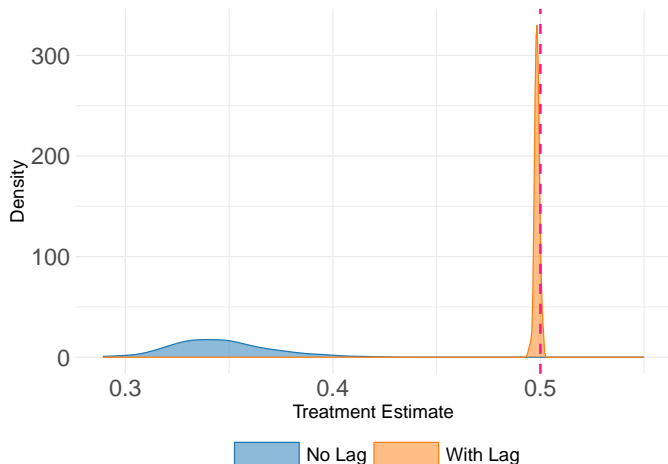
- Instead of running **Static Model** I suggest a **Dynamic Model**.

$$\text{Static Model : } \text{GDP}_{i,t} = \alpha_i \text{country}_i + \beta_2 \text{temperature}_{i,t} + \epsilon_{i,t}. \quad (3)$$

$$\text{Dynamic Model : } \text{GDP}_{i,t} = a_i \text{country}_i + b_2 \text{temperature}_{i,t} + \rho \text{GDP}_{i,t-1} + u_{i,t}. \quad (4)$$

- Researchers often avoid the **Dynamic Model** due to concerns about Nickell bias [Nickell, 1981].
- But **Static Model** leads to more bias than the **Dynamic Model** (my paper).

Distribution of Estimates: Static (No Lag) vs Dynamic Model (With Lag)



- Generate 1000 datasets based on DGP.^a
 - treatment = .5.
- Estimate treatment with both models.
- Bias of static model (no lag) is **dynamic bias**.
- Bias of dynamic model (with lag) is **Nickell bias**.

^a $\rho_{0,1} = .95$, Number years = 30

Bias Correction

- The **Static Model** introduces greater bias than the **Dynamic Model**.
- I suggest run the **Dynamic Model**.

Dynamic Model :
$$\text{GDP}_{i,t} = a_i \text{country}_i + b_2 \text{temperature}_{i,t} + \rho \text{GDP}_{i,t-1} + u_{i,t}. \quad (5)$$

- Treatment still has small Nickell bias.
- I propose a new estimator with an analytical bias correction method effective even for shorter time series, maintaining small standard errors.

Implications for Practice

- Many environmental contexts when **past outcomes** impacts current outcomes.
- The biases discussed increase under the following conditions:
 - Fewer time periods in your data.
 - The larger the effect of the past outcome.
- Simply modeling time trends does not control for dynamics.
- When working with panel data, include past outcome, even if the treatment (e.g., climate shocks) is random.

Next Steps and Current Work

- Explore biases arising from spatial dynamics, not just temporal dynamics.
- I work on econometric and statistical tools for environmental questions.
 - My research applications focus primarily on agricultural economics.
- I develop estimators that use high-dimensional data and machine learning for flexible modeling in panel and spatial data.

Thank you for your time!

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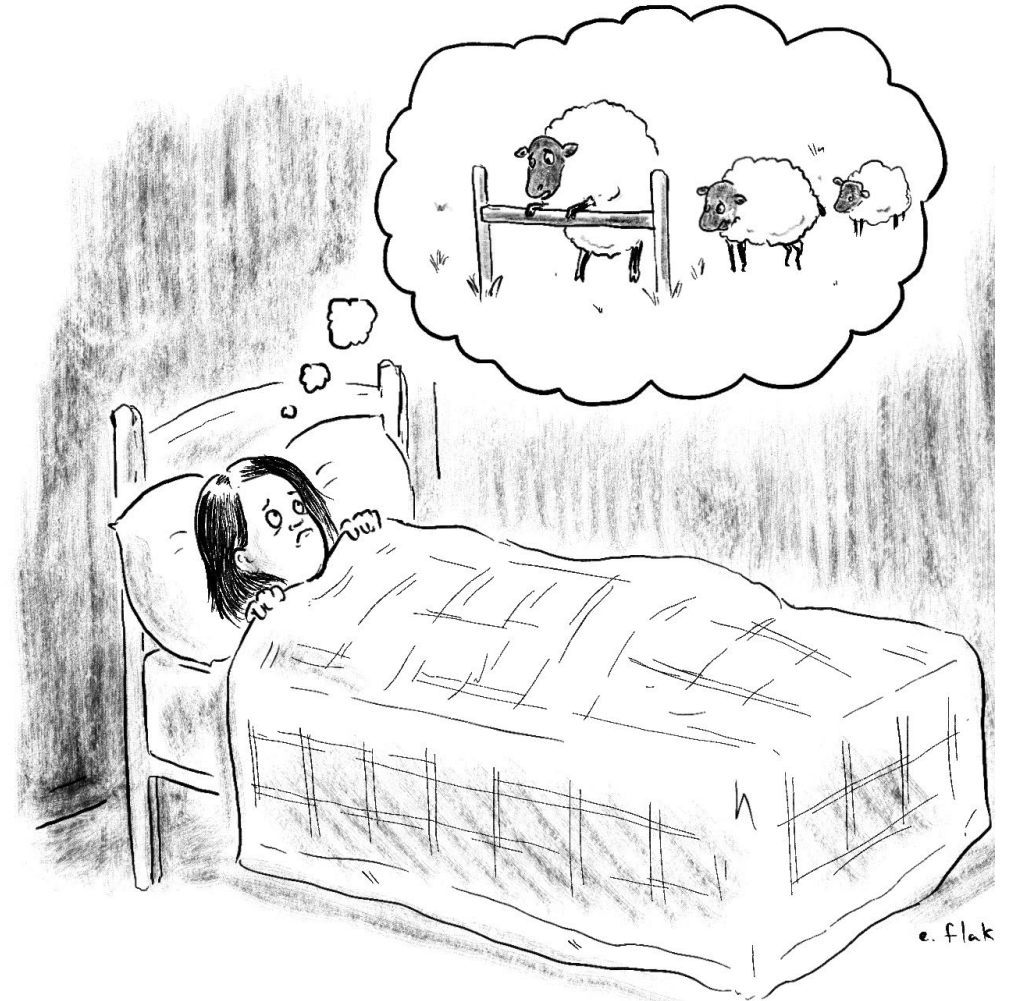
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Model-based predictions of unprecedented extreme weather

Erin Coughlan de Perez, PhD
Tufts University
Red Cross Red Crescent Climate Centre



"Yeah, we're pretty freaked out too."

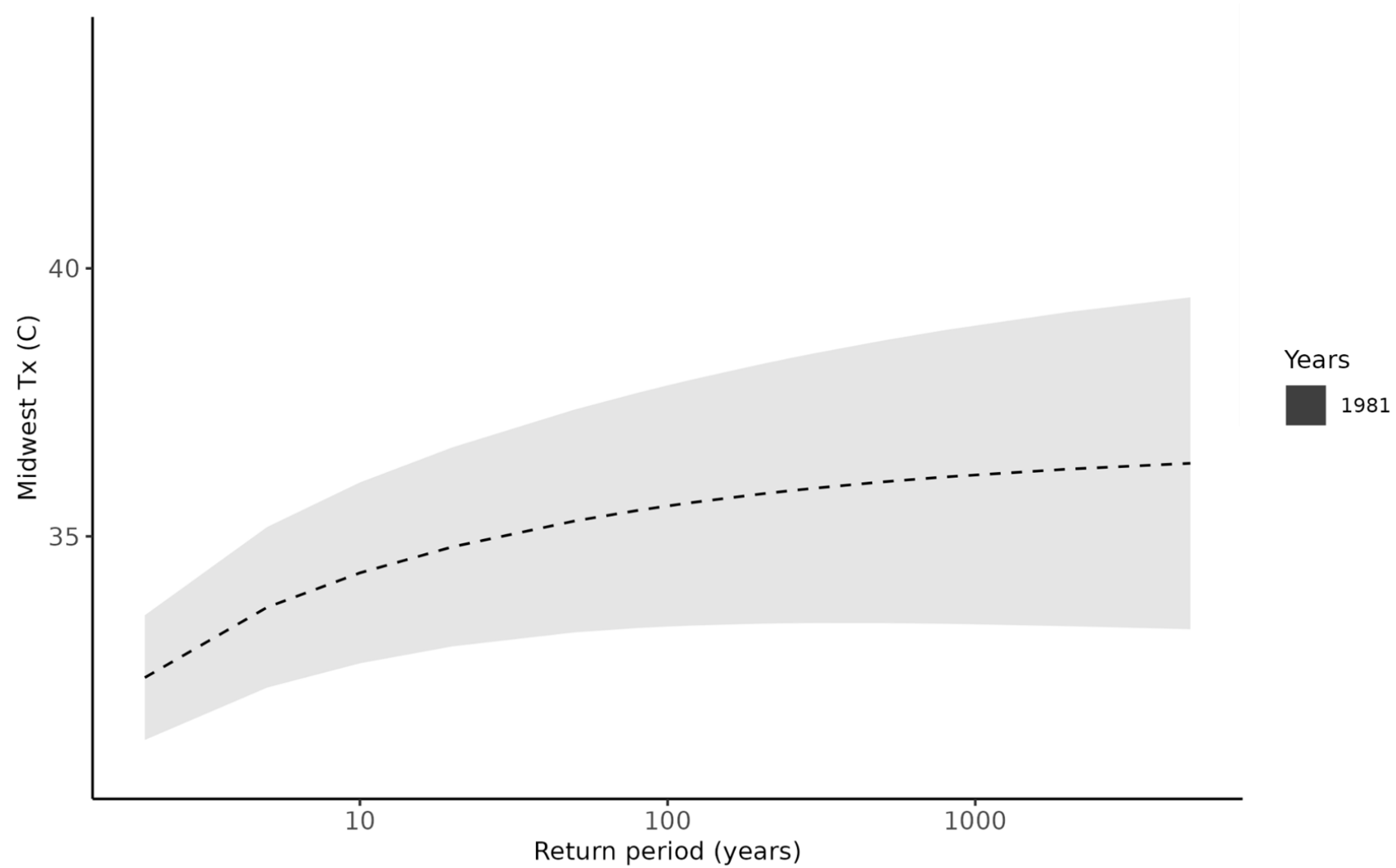
Studying extreme
events is a
challenge



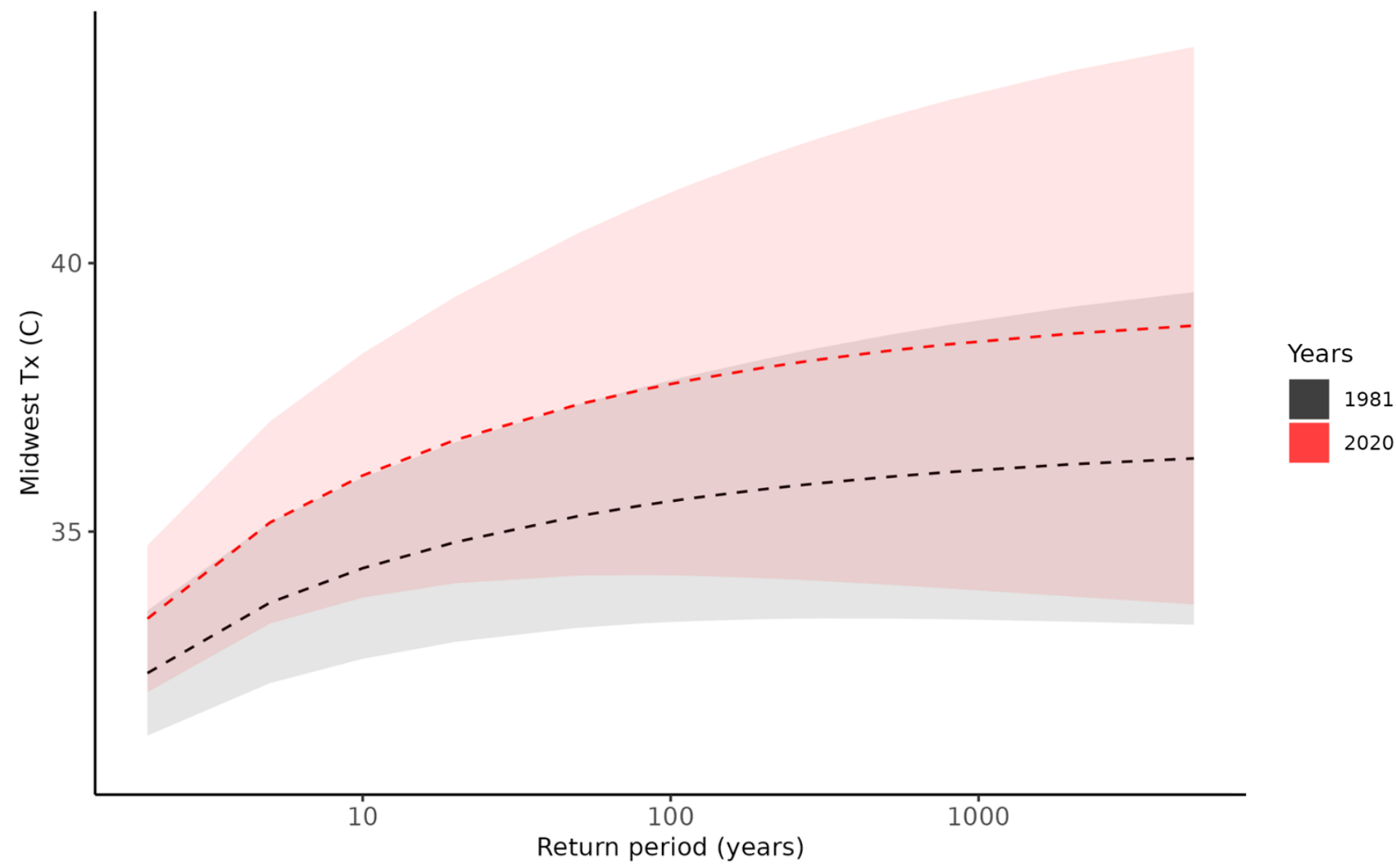
If you wanted to
estimate return
period of an
extreme heat event
using only
observations



1981



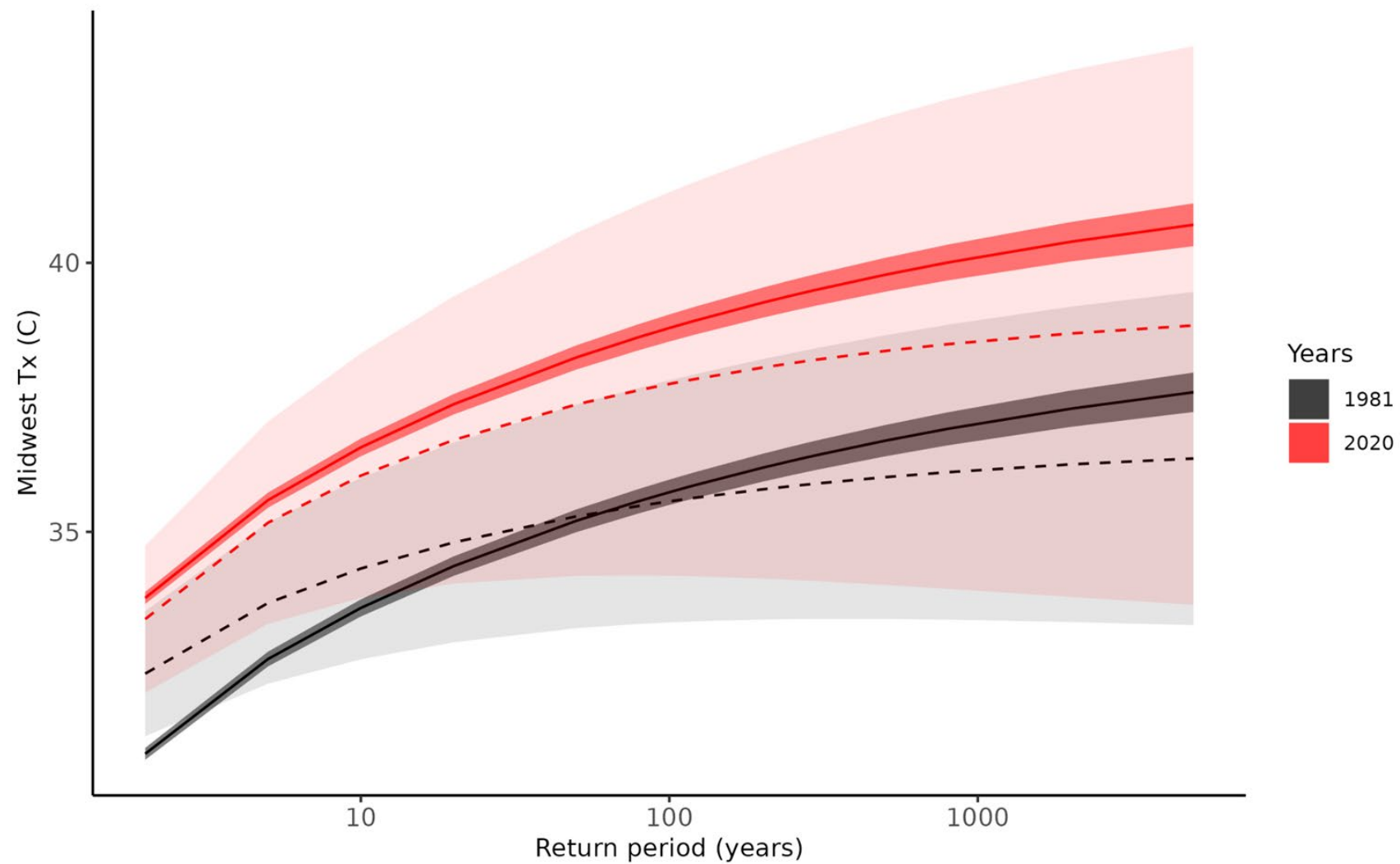
2020



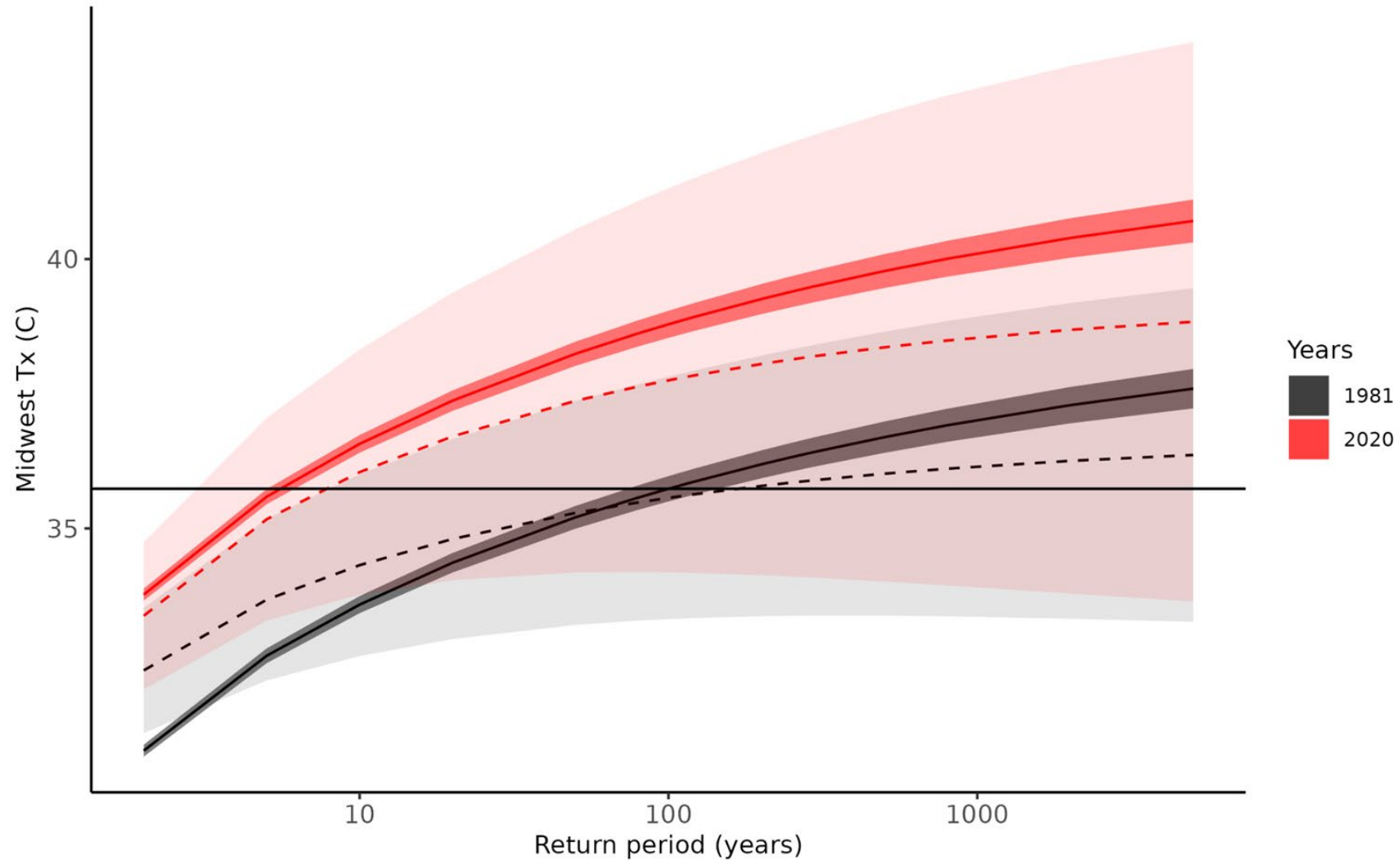
UNSEEN approach



Estimates from large ensemble



Change in risk



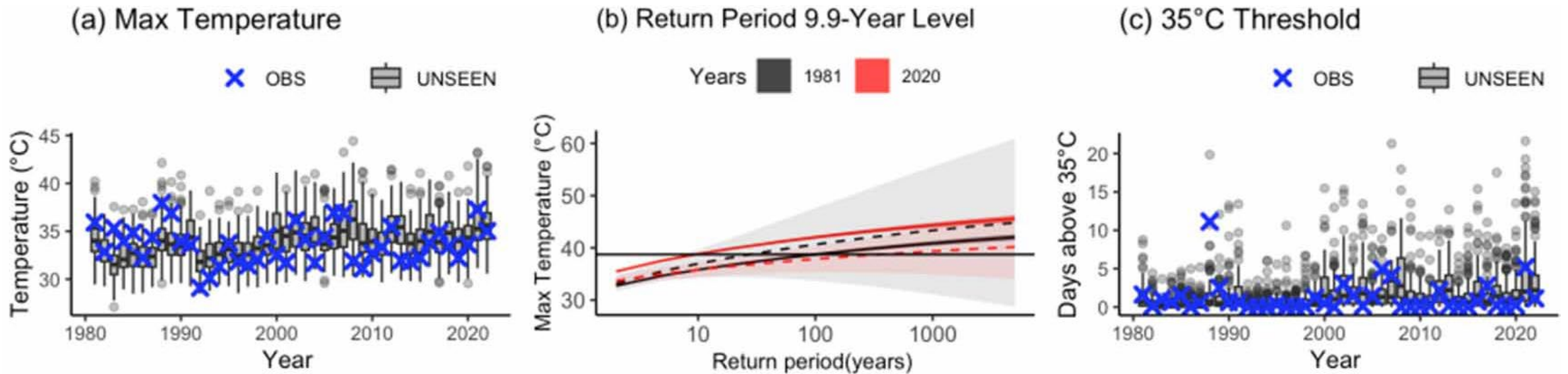
How is this useful
in the food system?
What can we do
with large numbers
of simulations?



1. What to plant:
risk of exceeding
stressful
thresholds



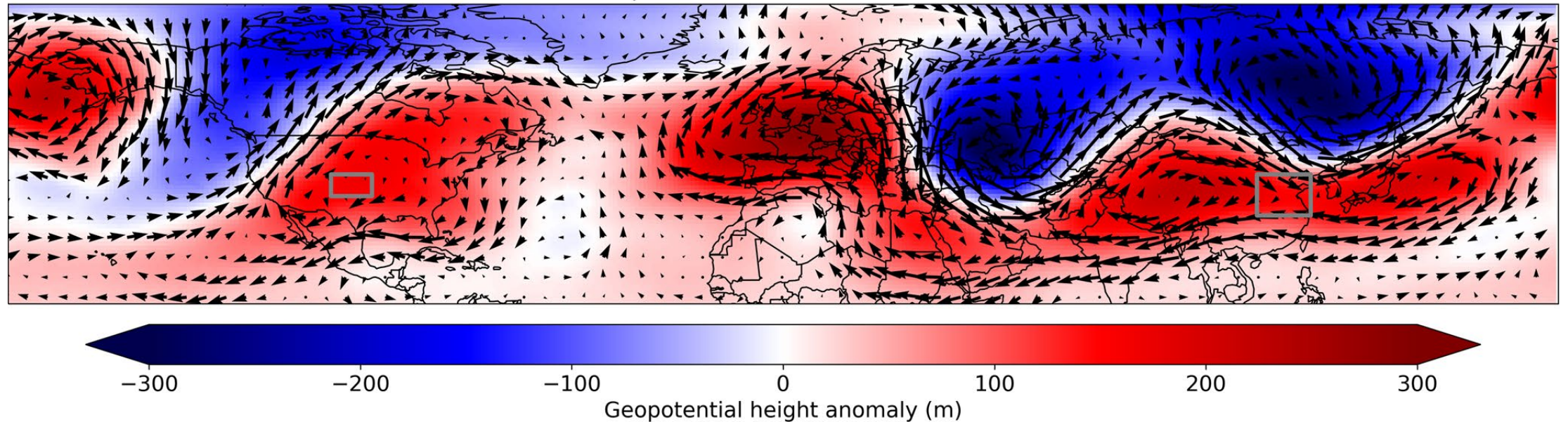
Crop choices: Pulse production in North Dakota



2. What to source?
Risk of
simultaneous
extremes and crop
failure in different
parts of the world



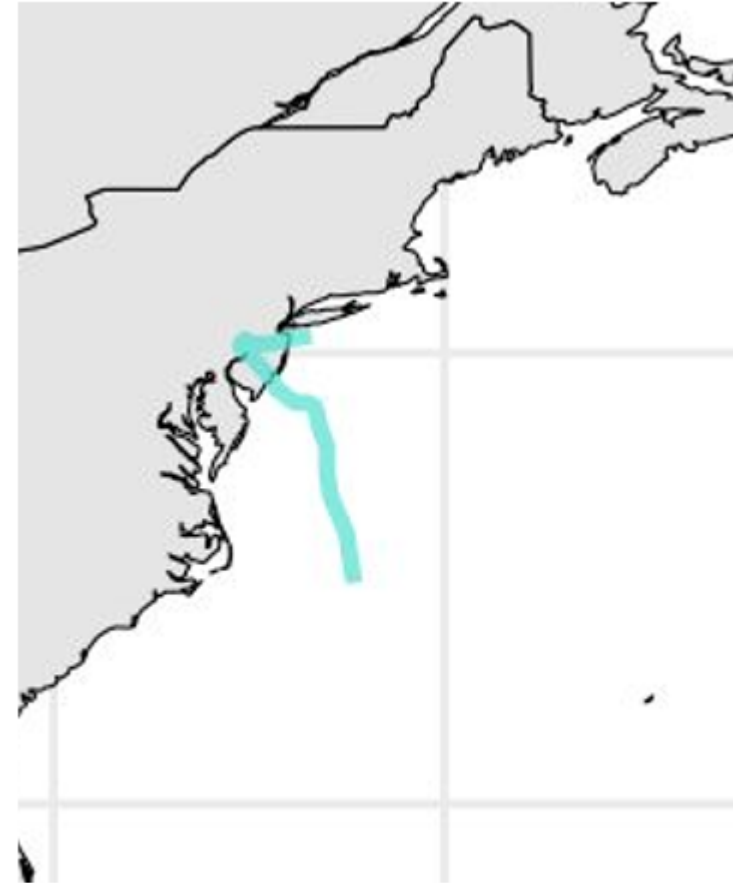
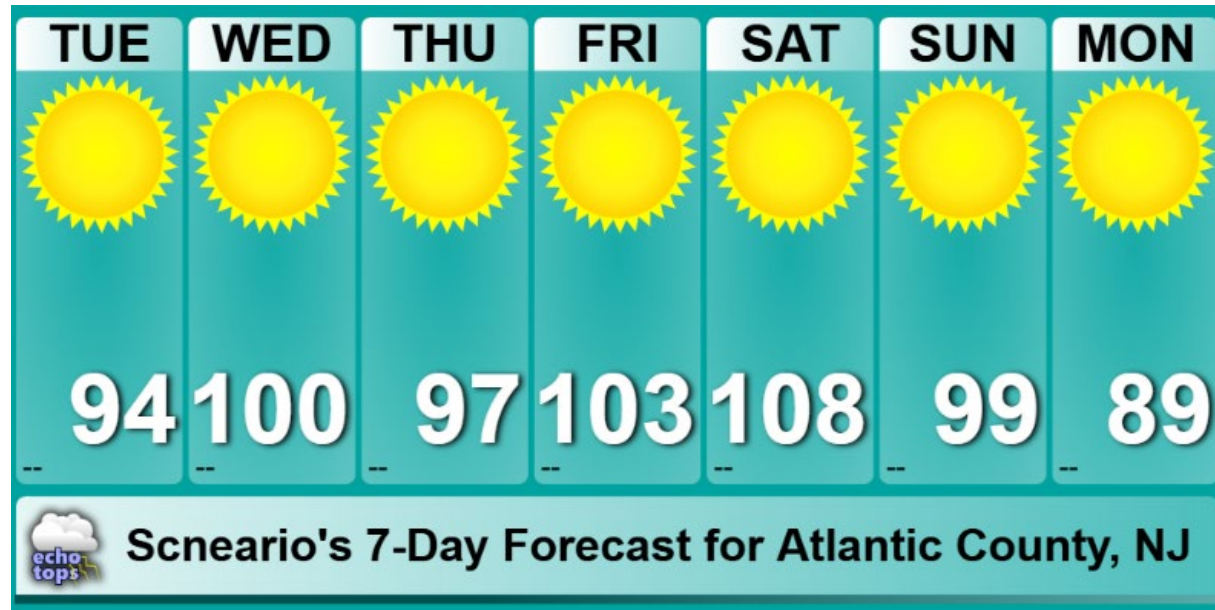
Supply chain management: Risk of compound events



3. What to prepare for? How could these extreme weather events unfold?



Disaster management: Scenario exercises

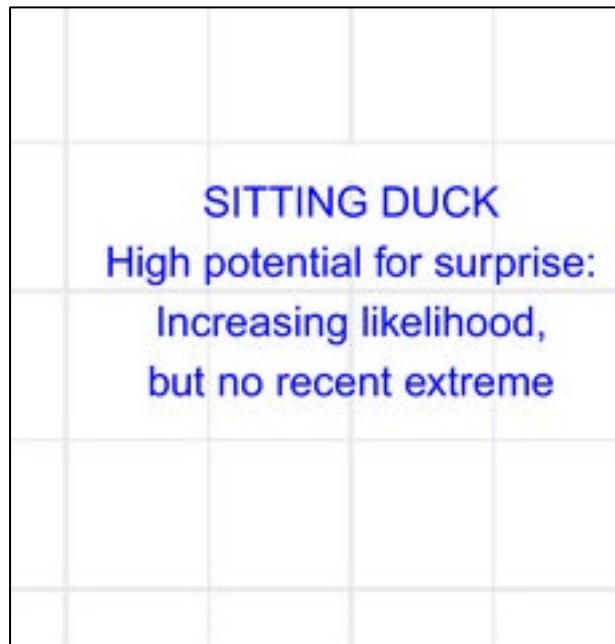


Track of Hurricane Eleanor from
Sunday to Tuesday

4. Where are the locations at greatest risk of an extreme event?



Where do we need to do risk management: Sitting ducks



Total Recycling for Food Production in Space

Taylor Lanosky

May 2, 2025

Benefits of space travel include...

Advances in science
and engineering

Benefits to humanity

Exploration and
inspiration

Potential refuge from
Earth

Benefits of space travel include...

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inspiration

**Planned long-term space missions are
impossible due to lack of resource
availability, especially food**

Benefits to humanity

Potential refuge from
Earth

It is currently impossible to feed astronauts on long-term space missions



The ISS stocks ~3.8 lb of food per astronaut per day



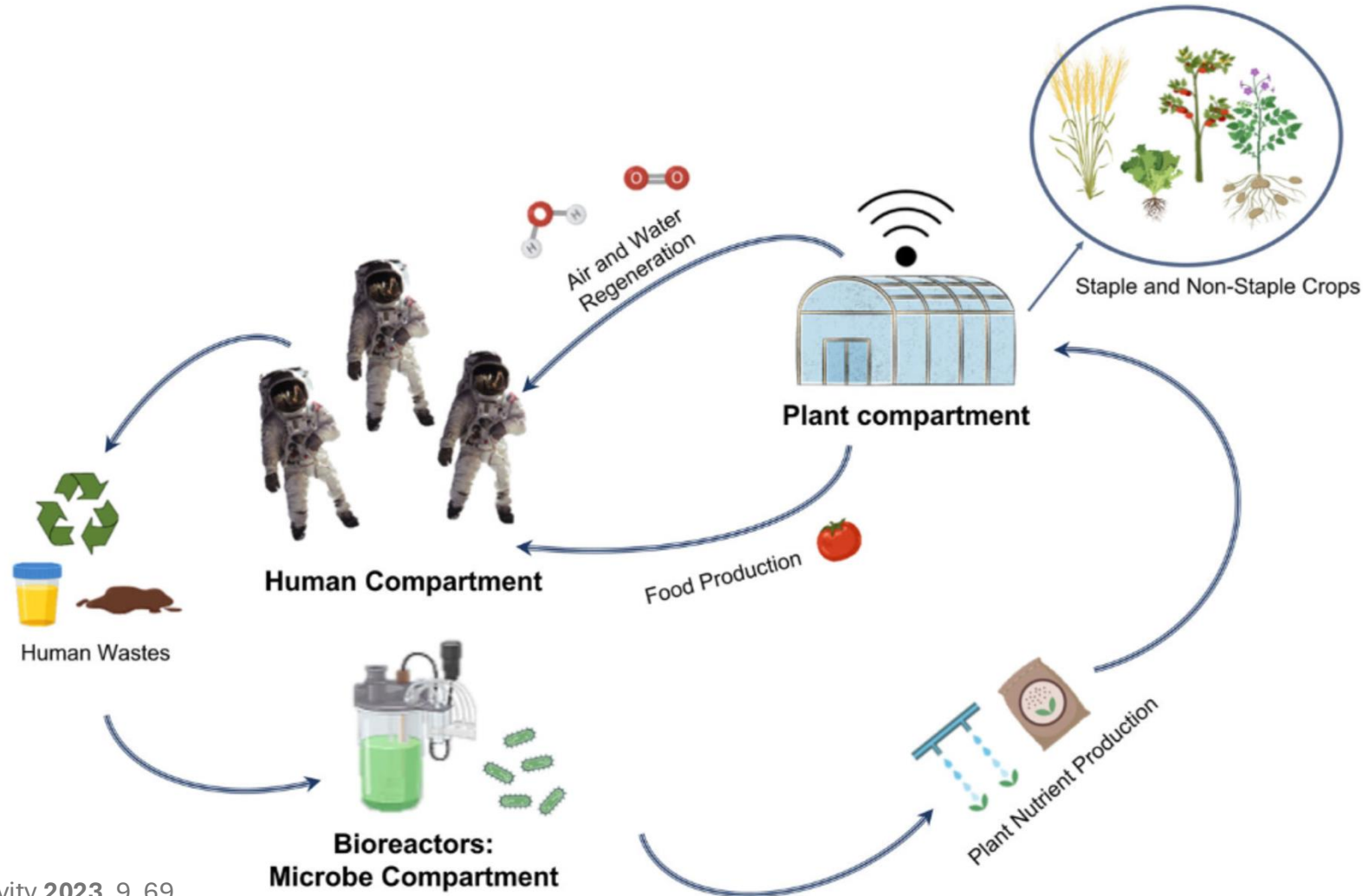
Space travel has very strict mass/volume limitations



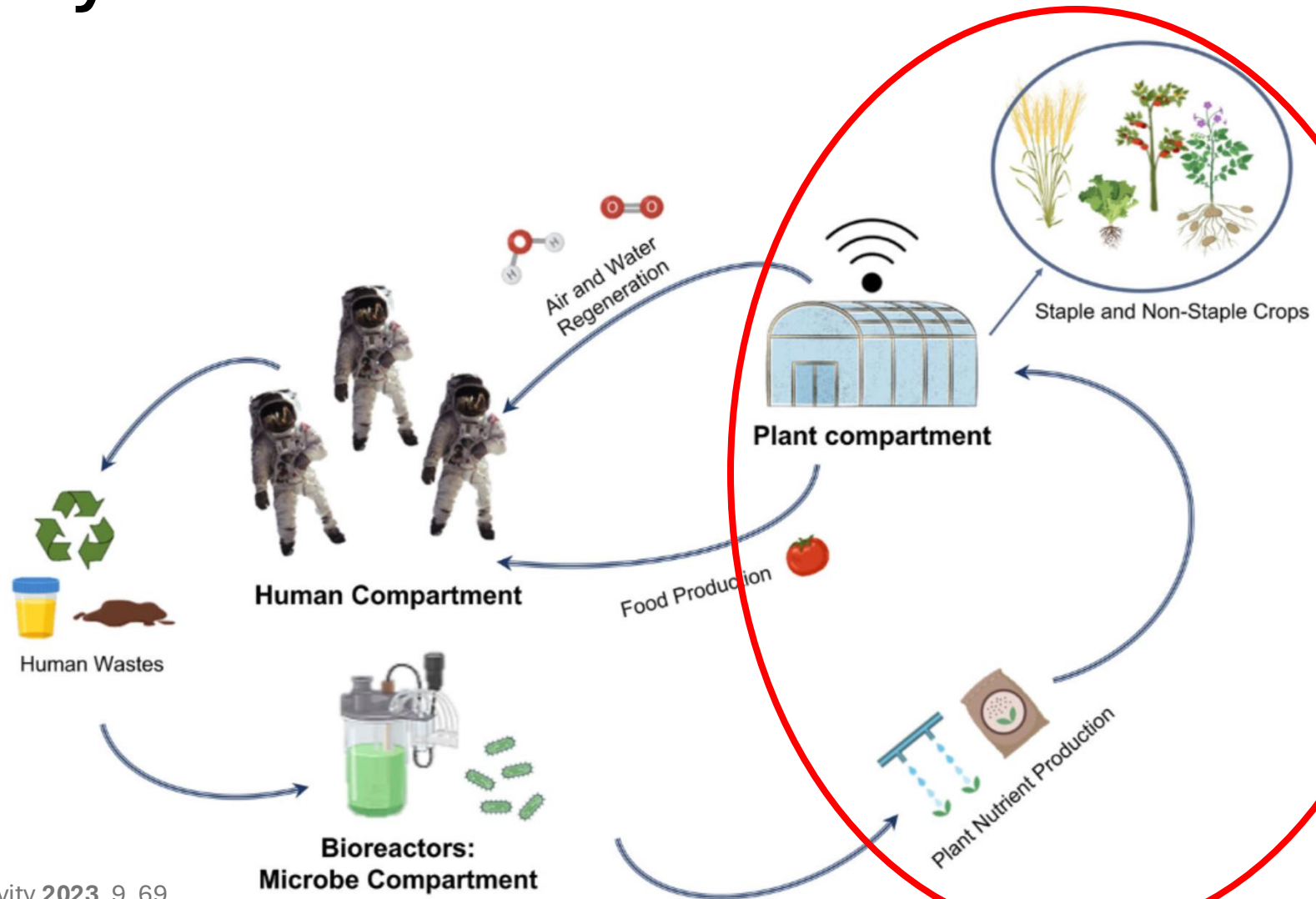
Pre-packaged food has a short shelf life and is unpalatable → astronauts eat 25-30% less in space

Solution: Bioregenerative food production systems

Bioregenerative life support systems produce and recycle all resources needed for survival

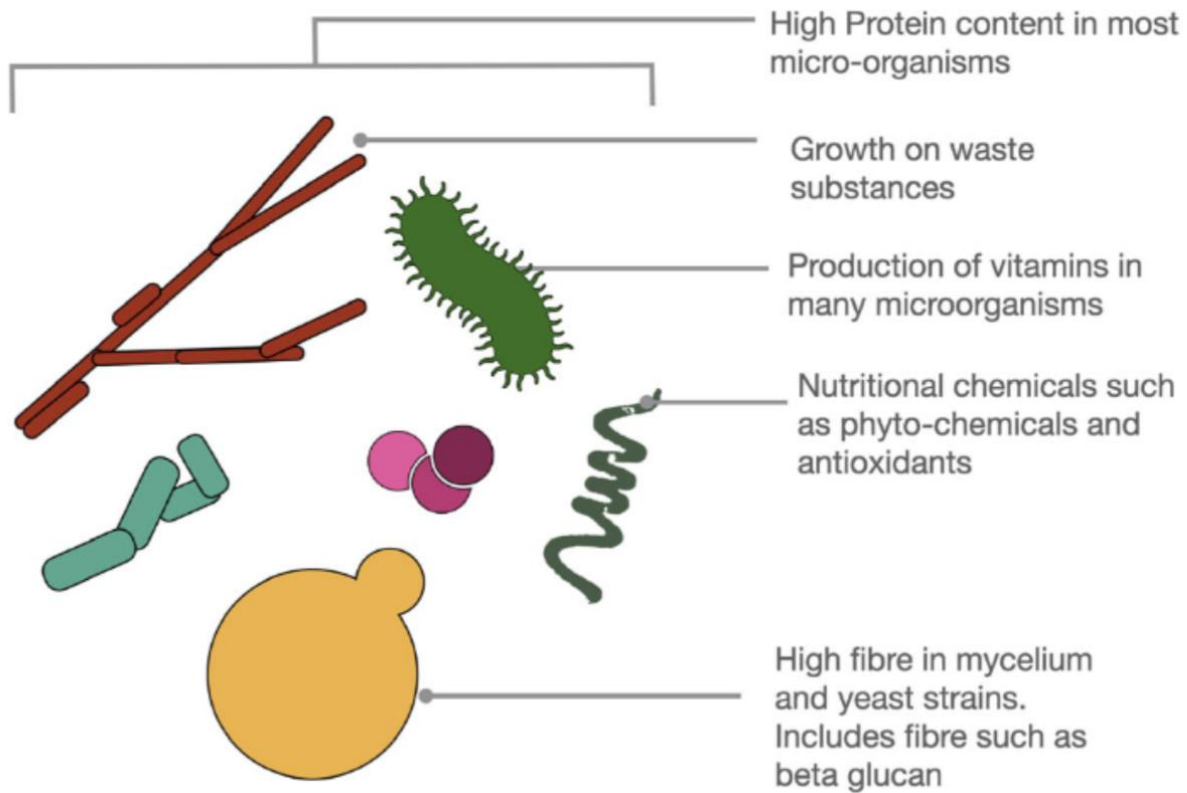


Bioregenerative life support systems produce and recycle all resources needed for survival



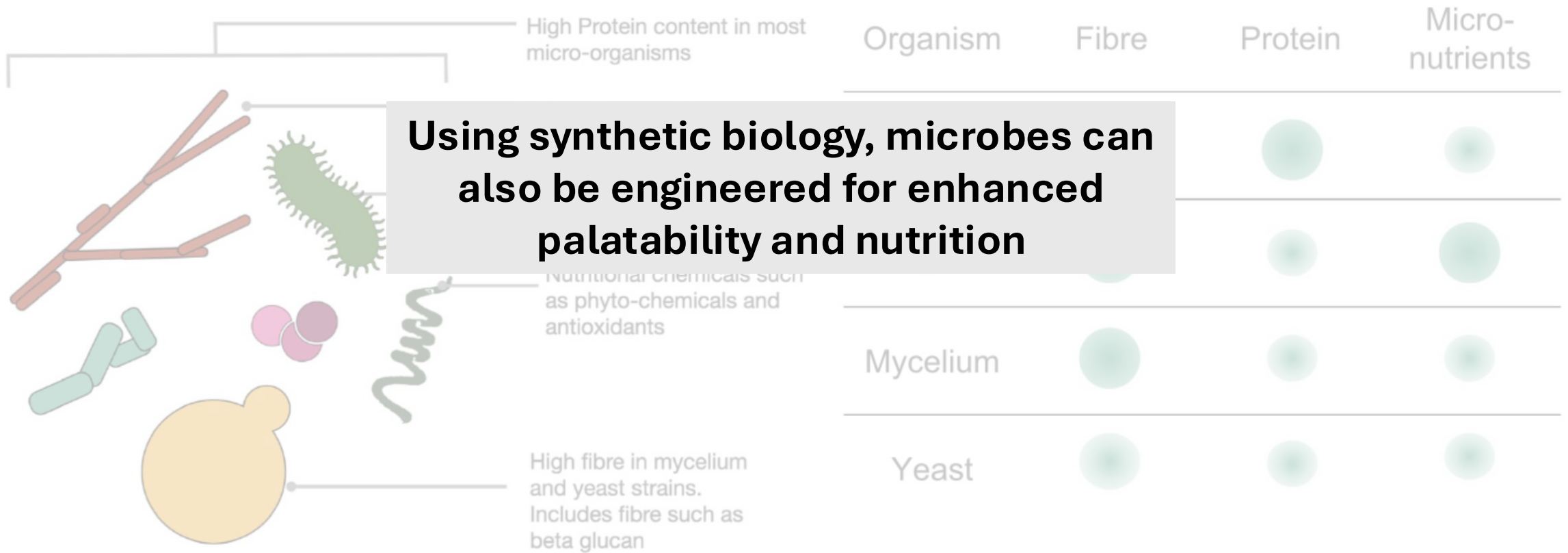
Requires too much space, limited by photosynthetic efficiency

Microbes generally offer a good source of nutrients

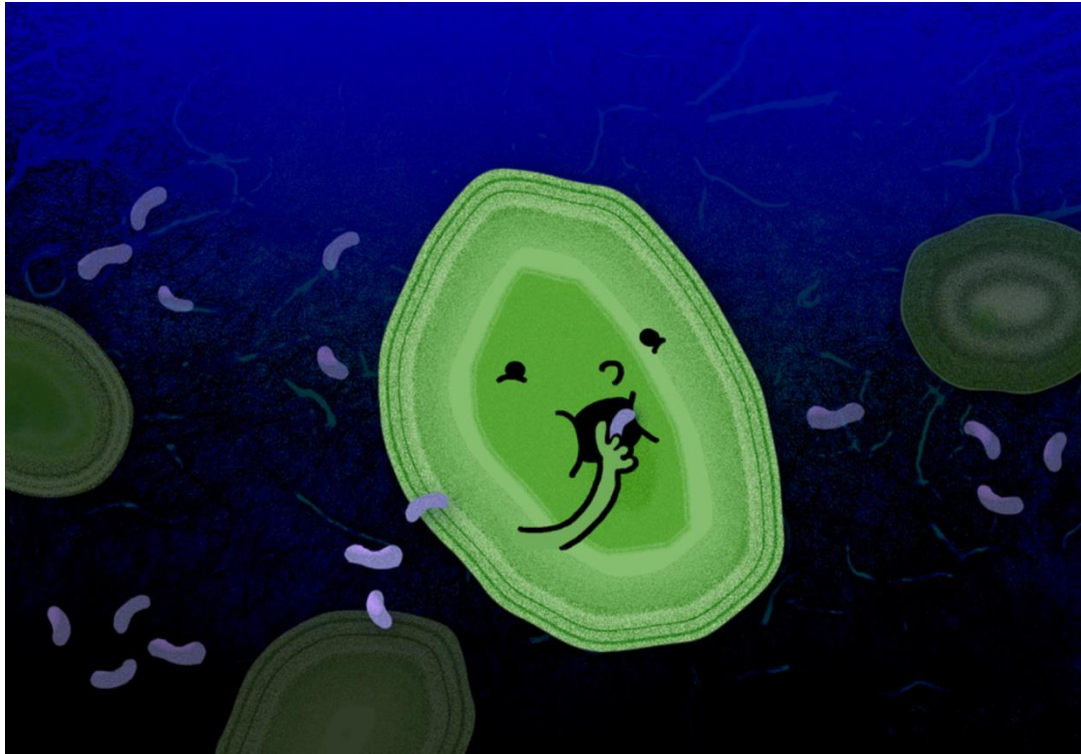


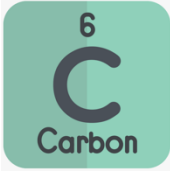

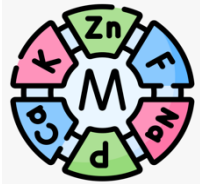
Organism	Fibre	Protein	Micro-nutrients
Bacteria			
Algae			
Mycelium			
Yeast			

Microbes generally offer a good source of nutrients

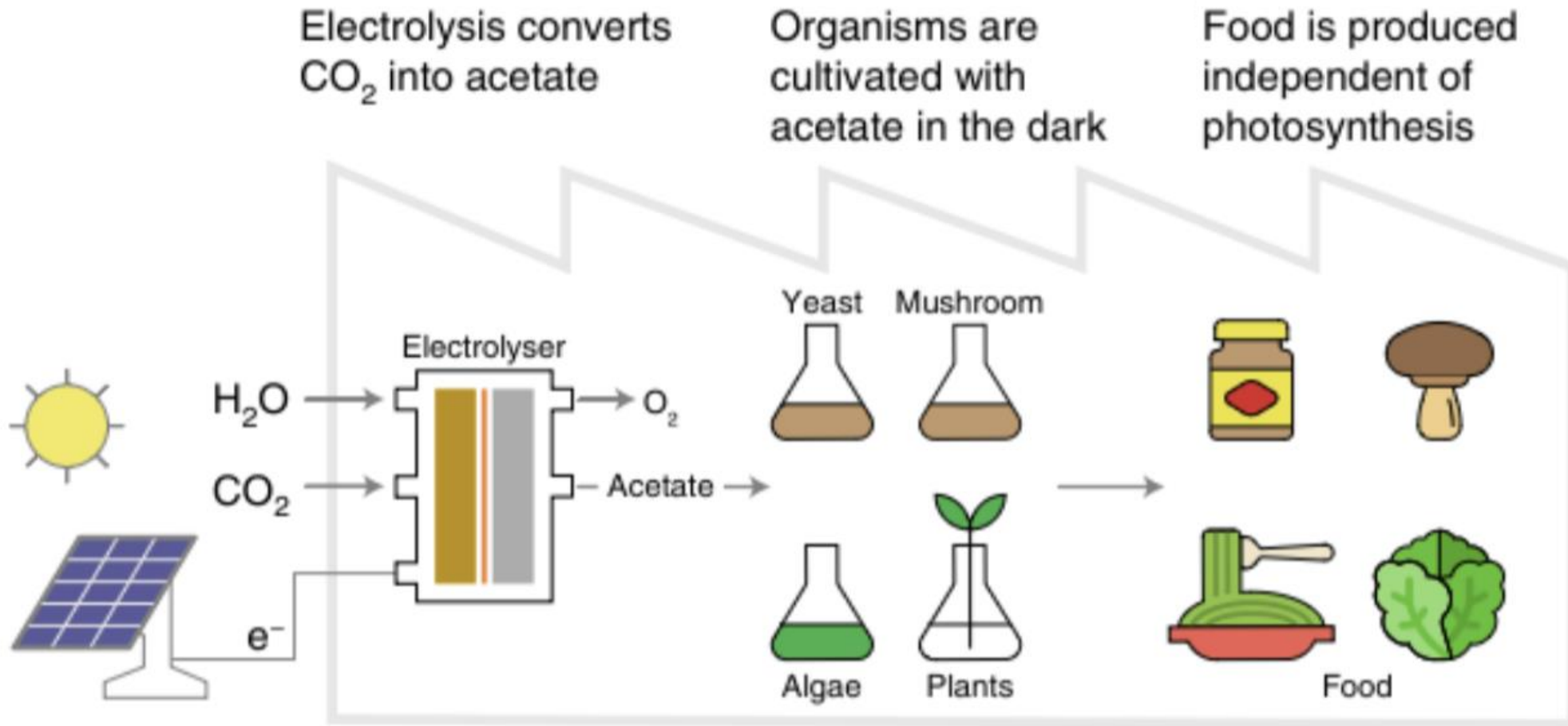


Nutrients for microbial growth must come from readily available and sustainable sources

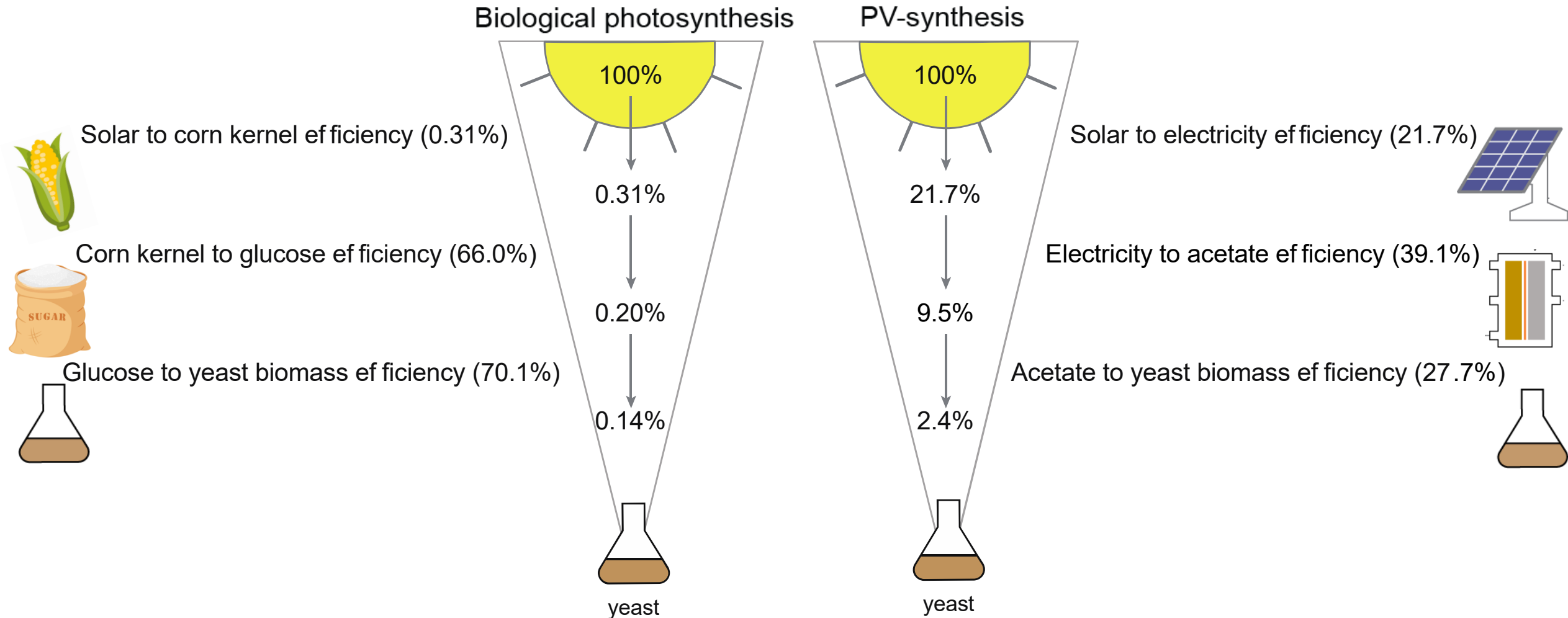


Necessary Nutrient	Proposed Source
	Electrolytically produced acetate
	Processed fecal matter
 Minerals	Processed fecal matter

Electrolytically produced acetate offers a sustainable carbon source that is efficiently generated

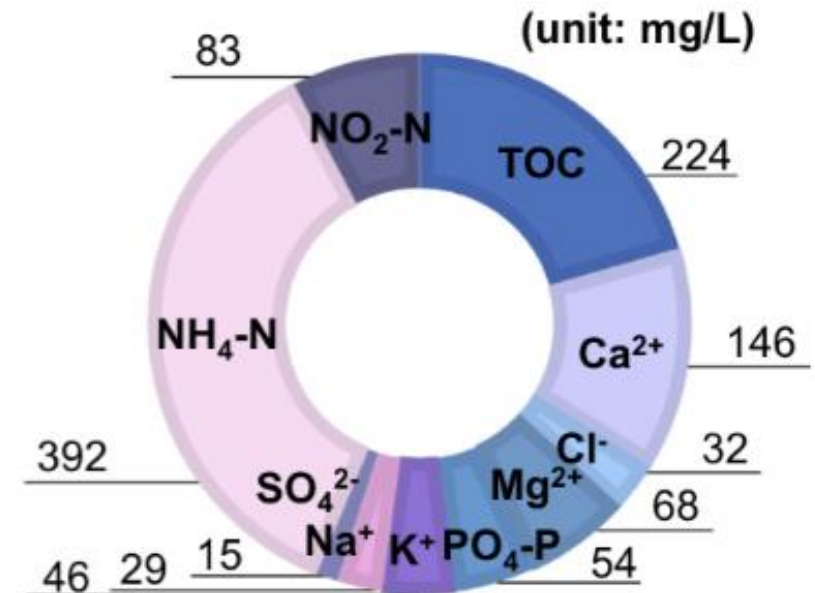
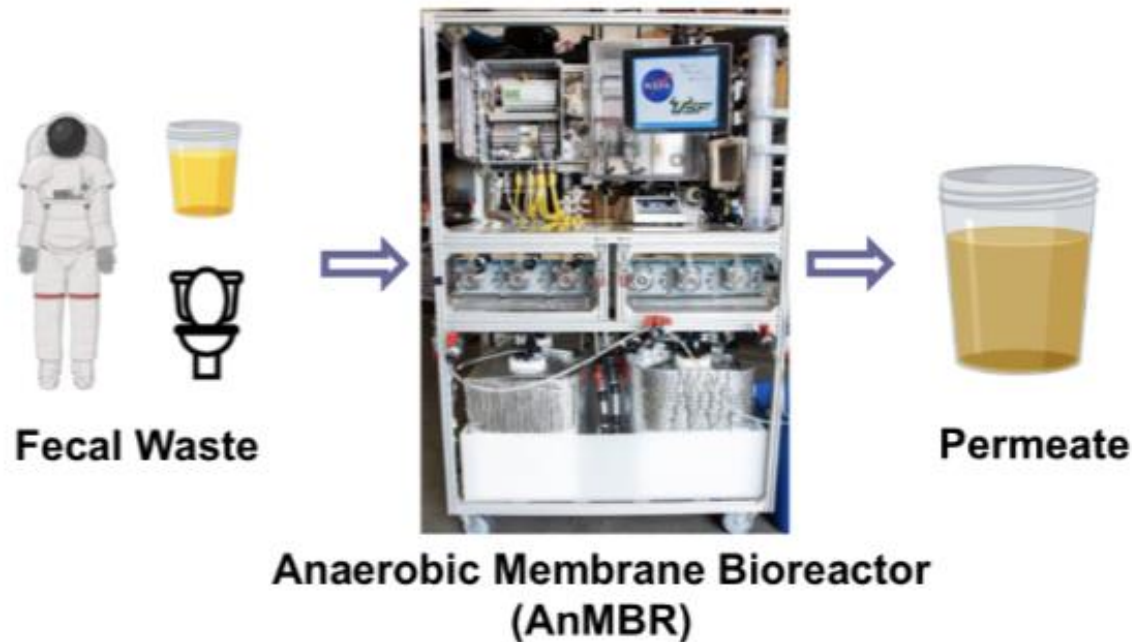


Solar-to-biomass conversion efficiency of yeast cultivation is improved almost 18-fold

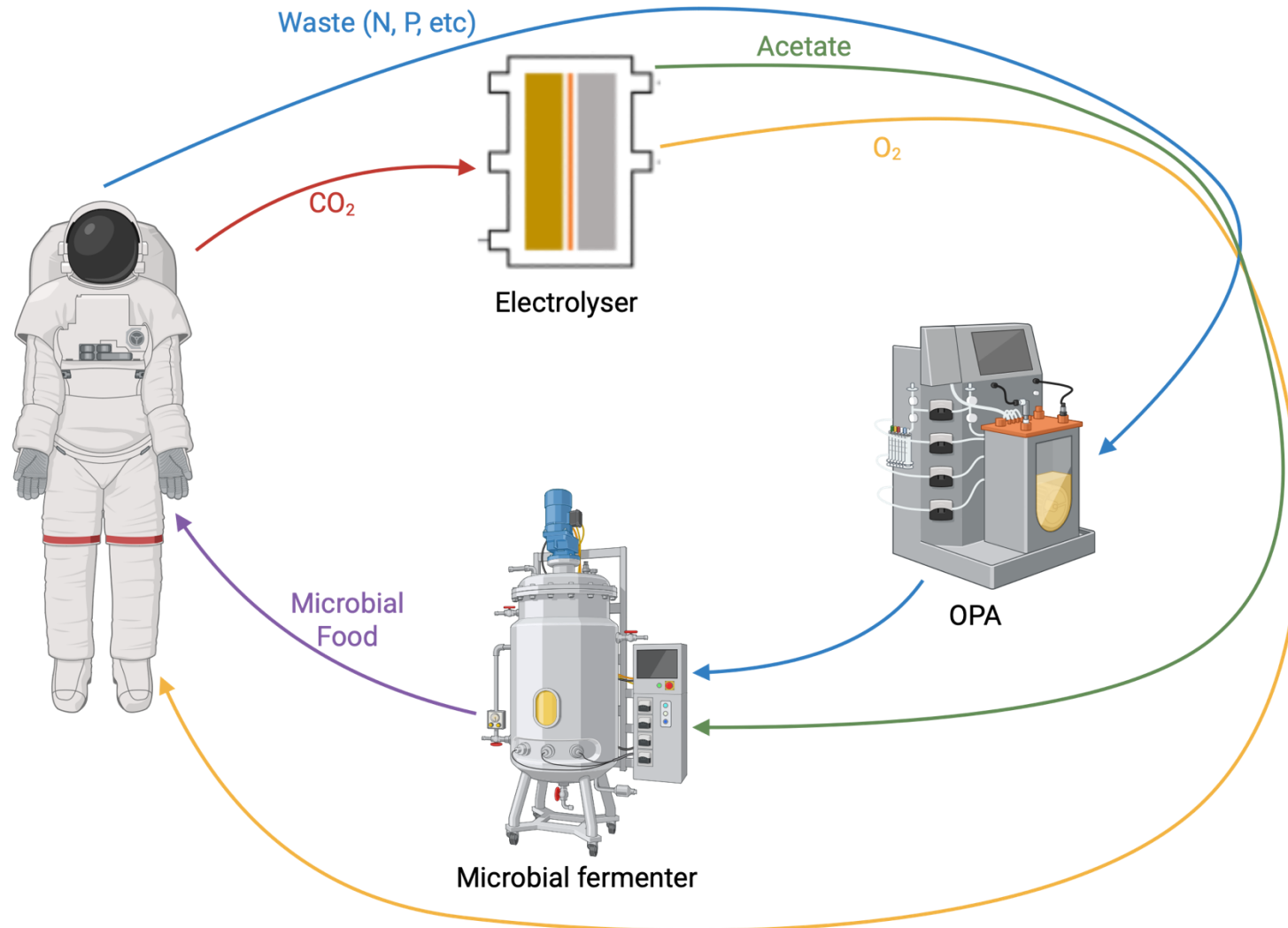


Fecal waste can be processed using the Organic Processor Assembly (OPA)

- OPA: Combines anaerobic digestion with membrane filtration to produce a high-quality, nutrient-rich, pathogen-free effluent
- Can process 2.5 L of human waste per day to generate 2.5 L of effluent (permeate)



Microbes grown on electrolytically produced acetate and fecal permeate could be an efficient food source in space



While designed for space, this closed loop also offers a sustainable food solution on Earth



- Useful in any low resource setting
 - Malnourished countries
 - Military missions
 - Long-term missions to the deep sea
 - Colonization of inhospitable areas
 - Crisis response
 - Controlled research studies, etc.

Thank you!

Questions?

Climate Change and Fisheries Exploitation

Global Food+ Symposium

Andrés de Loera

May 2, 2025

Fisheries Under Climate Change

- ▶ Ocean warming directly decreases fisheries biomass by reducing fish sizes and population growth.
 - Warming decreased yields by 4.1% from 1930-2010 (Free et al., 2019)
 - Ocean acidification also directly or indirectly decreases total biomass on net (Branch et al., 2013)

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- ▶ Climate change also induces shifts in fishery ranges as fish seek environmental conditions they are adapted to. (Kleisner et al., 2017; Dahms and Killen, 2023)
 - Distinct from biomass decline (Chaikin et al., 2024)

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 - Distinct from biomass decline (Chaikin et al., 2024)
- ▶ A significant share of the world's fisheries are “transboundary” (Palacios-Abrantes et al., 2020)
- ▶ Climate change may threaten these transboundary stocks, as countries anticipating they will lose their fish resources may harvest more from them now, even if globally suboptimal.
 - *Maladaptation* to climate change.

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- ▶ Climate change may threaten these transboundary stocks, as countries anticipating they will lose their fish resources may harvest more from them now, even if globally suboptimal.
 - *Maladaptation* to climate change.
- ▶ **What are the endogenous policy responses to climate-induced range shift? What are their consequences?**

Theoretical Predictions

- ▶ Every year, fisheries managers observe the stock and decide how many fish to catch
 - ⇔ decide how many fish from a stock *not* to catch = Escapement
- ▶ Optimal escapement equates marginal profit in this period with return to fisheries productivity in future periods.
- ▶ But, each country internalizes only the returns to fisheries productivity that will accrue in their own waters.
 - Privately optimal escapement < globally optimal escapement in transboundary fisheries.

Theoretical Predictions

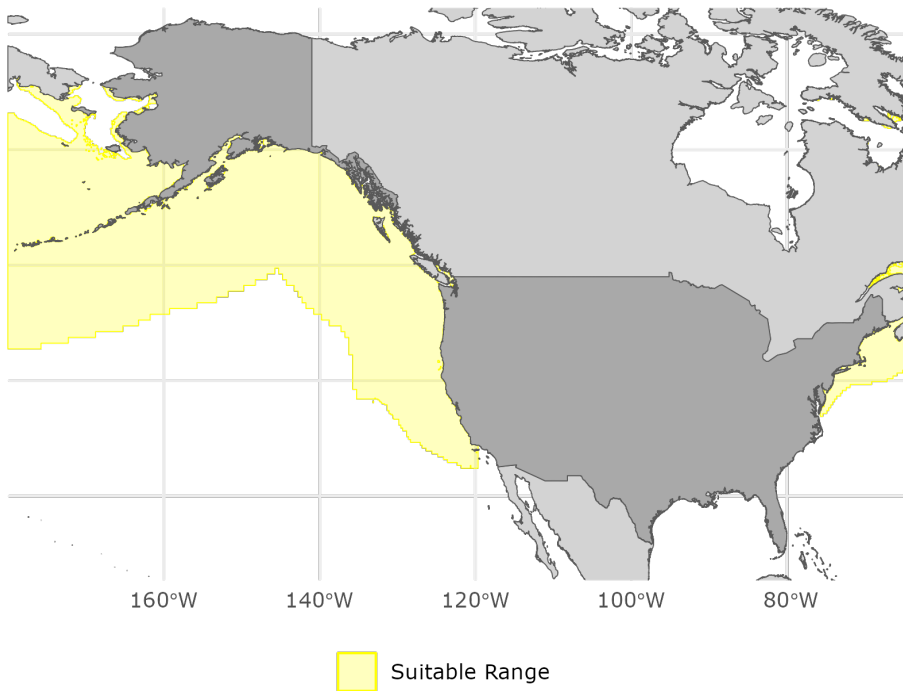
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- ▶ Optimal escapement equates marginal profit in this period with return to fisheries productivity in future periods.
- ▶ But, each country internalizes only the returns to fisheries productivity that will accrue in their own waters.
 - Privately optimal escapement < globally optimal escapement in transboundary fisheries.
- ▶ Climate change exacerbates this problem in the short run, by creating lower returns to escapement from shifting stocks.
- ▶ Climate change *could* exacerbate this problem in the long run, if it increases the amount or degree of transboundary fisheries.

Data

- ▶ Data on fisheries extraction from the RAM Stock Assessment Database.
 - Database of catch, biomass, and other stock assessment results.
- ▶ Construct escapement for 328 stocks from 1982 to 2024.

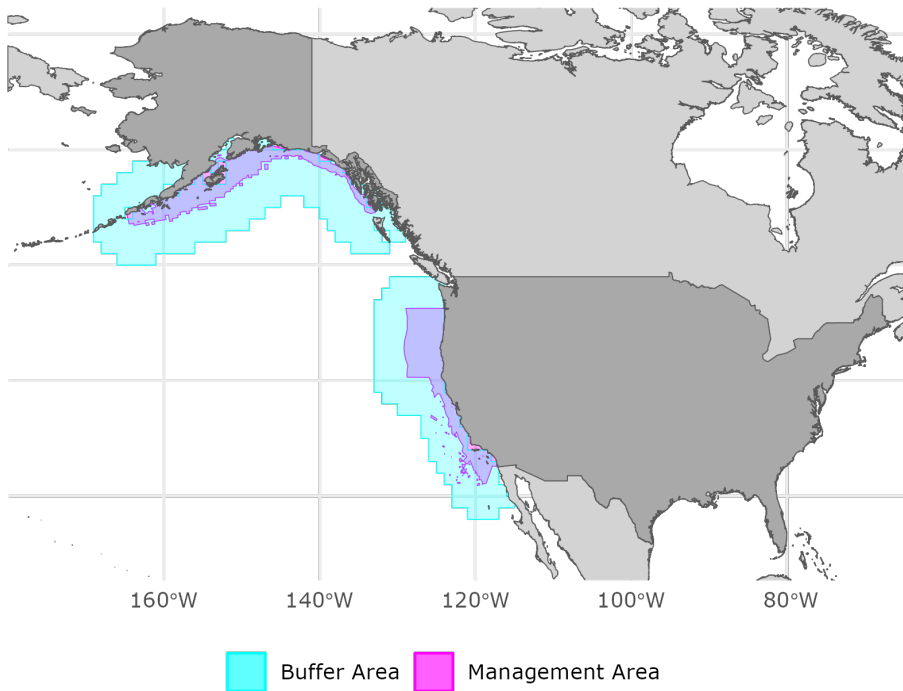
Data

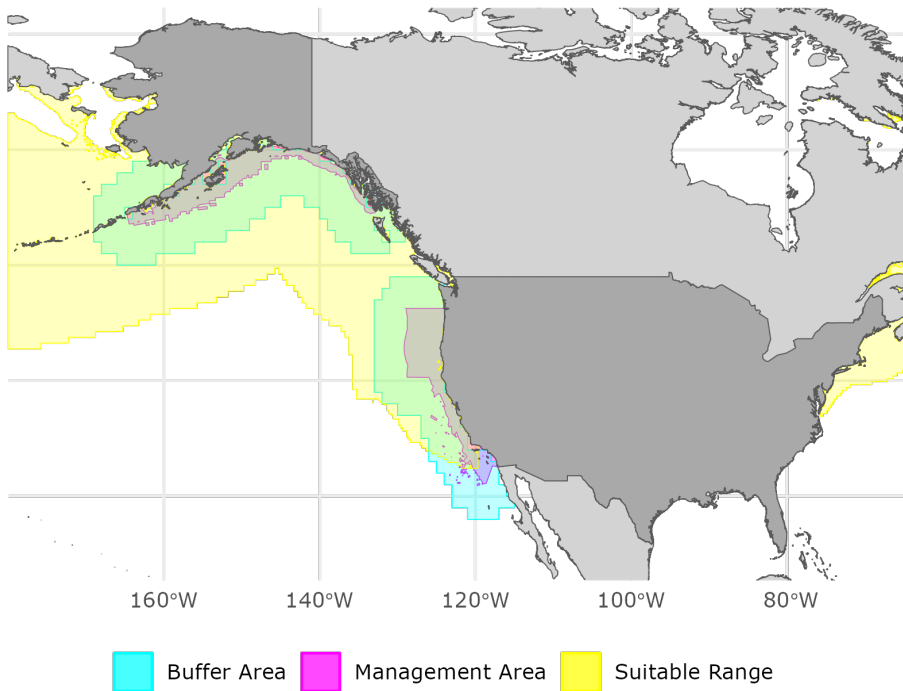
- ▶ Data on fisheries extraction from the RAM Stock Assessment Database.
 - Database of catch, biomass, and other stock assessment results.
- ▶ Construct escapement for 328 stocks from 1982 to 2024.
- ▶ I do not have a panel of fish stock ranges.
- ▶ Instead, I construct an annual “suitable habitat” raster and look at changes in areas around known stocks.
 - Suitable habitat based on bioclimactic envelope from AquaMaps: If an area is between the minimum and maximum for every environmental variable, I consider it suitable.
 - Variation comes from annual variation in Sea Surface Temperature and decadal variation in Salinity.



Measuring Range Shift

- Finally, I want to calculate range shifts out of management areas.
- For each fishery:
 - 1) Identify the management area with the shapefile from the RAM Stock Assessment Database.
 - 2) Construct a 200 nautical mile buffer around the fishery shapefile.
 - 3) Find the overlap of that buffer area with the suitability raster.
 - 4) Calculate what share of the total suitable area in the buffer falls within the management area shapefile = **Stock Share**.





Empirical Strategy

- ▶ Main outcome of interest: Escapement.
 - = Tonnage of fish that is *not* caught: Biomass - Catch
 - I normalize by the average escapement rate for the stock due to differences in magnitude and measurement.
- ▶ I regress the extraction rate on the Stock Share, controlling for Stock and Year fixed effects:

$$\text{Escapement}_{it} = \beta \text{Stock Share}_{it} + \gamma_i + \lambda_t + \epsilon_{it} \quad (1)$$

- ▶ Leverage variation in the stock share trend over time within each fishery to identify effect of the stock share on escapement.
- ▶ If β is positive, then stocks with higher Stock Shares have higher escapement.

Results

<i>Dependent variable:</i>	
Normalized Escapement	
Stock Share	1.976*** (0.722)
Stock FE	Yes
Year FE	Yes
Observations	9,980
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

Conclusions

- ▶ Climate change will, on average, decrease the stock shares of the management areas studied here.
- ▶ For each management area, I calculate the predicted effect of the stock share change on escapement in tonnes in 2050.
 - $\text{Predicted Stock Share Change} \times \text{Coefficient on Stock Share} \times \text{Average Escapement}$
- ▶ Several managed fisheries will see large decreases in escapement; fewer will see increases.
- ▶ On net, total escapement will fall by 13 million tonnes, from an average of 122 million (10% decrease).
- ▶ However, the countries gaining fish should have some offsetting effect.
- ▶ Still: Evidence of a maladaptive response to climate change in fishing.

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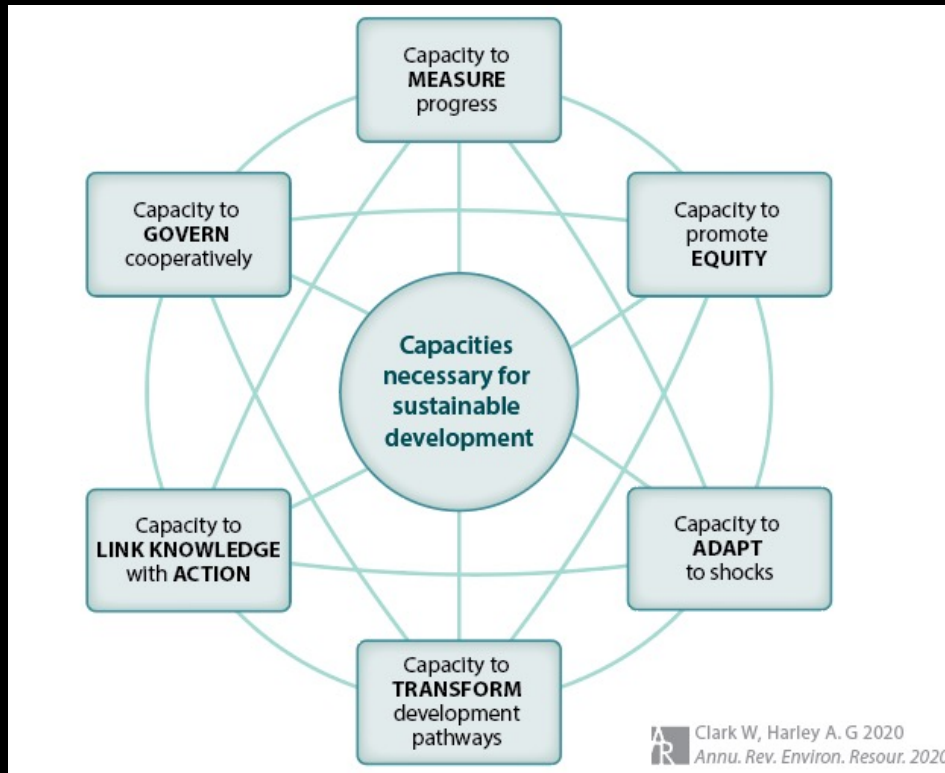


Building the Capacity to Promote Equity in Agricultural Innovation Systems:

Empirical perspectives from Bihar, India



Alicia G. Harley, PhD, Sustainability Science Program, Harvard Kennedy School
May 2, 2025

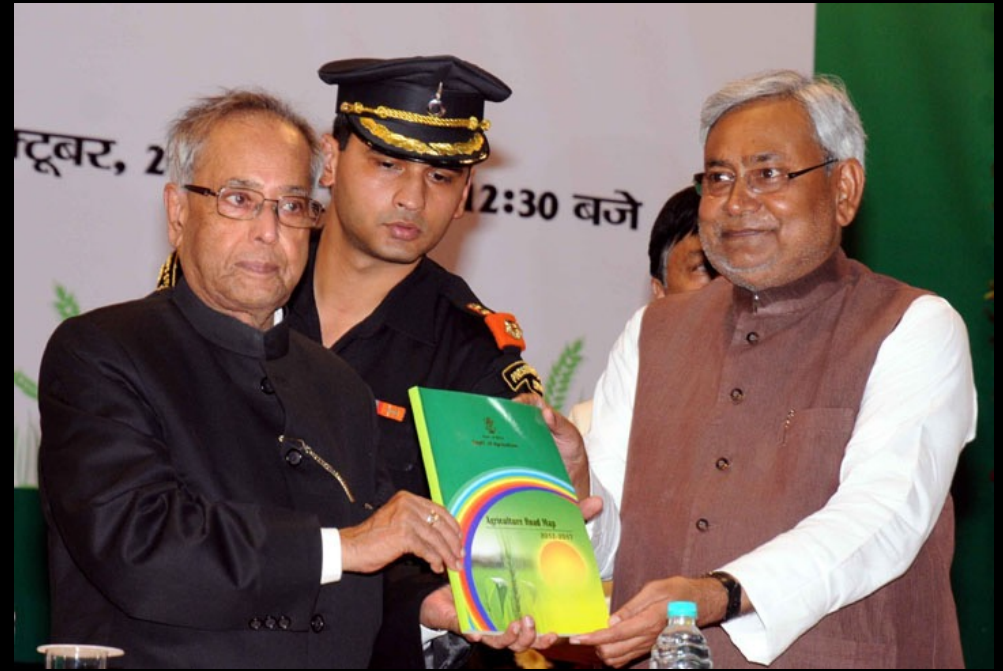
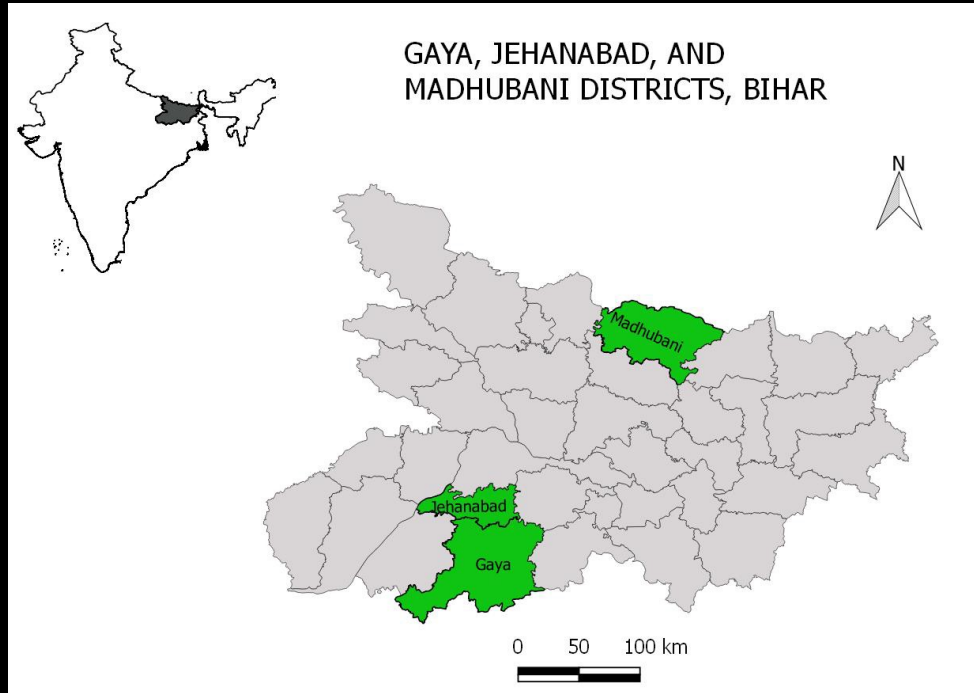


Six Capacities Necessary for the Pursuit of Sustainability



Capacity to
promote equity in
agriculture systems

What are the barriers preventing the poorest
farmers from realizing greater benefits from
agricultural technology?



A 21st century green revolution in
Bihar, India

Factor by which poorest farmers are less likely to use a technology than wealthier farmers

Number of Farmers in Category →	Caste Category Upper Caste (OBC and UC) - 248; Lower Caste (SC/ST) - 250	Landholding Size* Marginal (<2.5 acres) - 283; Non-Marginal (>2.5 acres) – 55
Technology	Factor by which a lower caste farmer is less likely to use a technology compared to an upper caste farmer	Factor by which a marginal farmer is less likely to use a technology than a non-marginal farmer
Diesel engine	1.01	1.16
Tractor	0.98	0.95
Improved seeds	0.93	0.92
Rubber pipes	0.89	0.93
Vermi-compost	0.69	0.31
Electrical motor pump	0.63 [^]	1.23 [^]
Intercropping	0.58	0.67
Introduced new crop	0.52	0.93
System of Rice Intensification	0.34	0.34
Drip Irrigation	NA	NA
Solar Irrigation Pumps	NA	NA

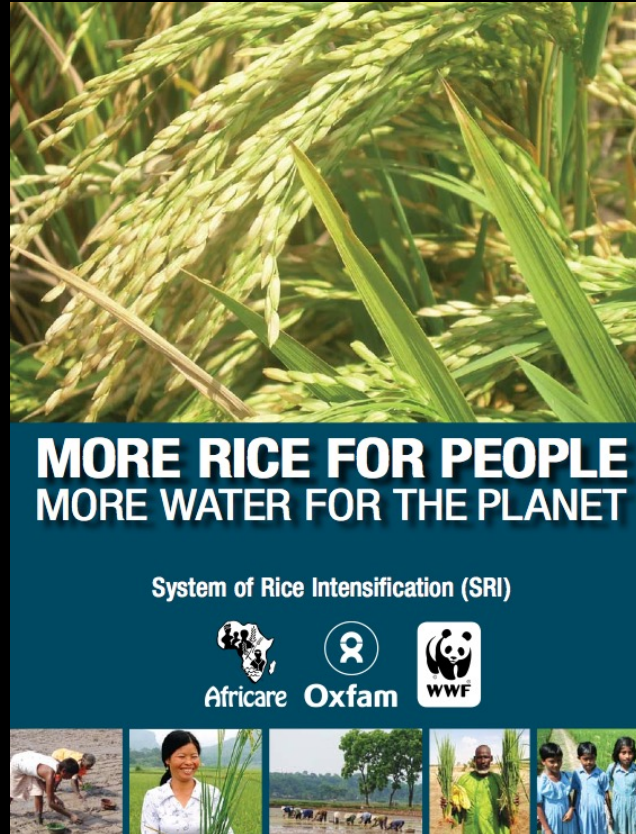
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Drip Irrigation	NA	NA
Solar Irrigation Pumps	NA	NA

Socio-technical Barriers to Technology Adaption

1. Lack of financial assets
2. Inappropriate technology design
3. Missing market linkages
4. Lack of access to credit
5. Missing infrastructure
6. Ineffective extension services
7. Lack of individual farmer capacity
8. Weak capacity for collective action
9. Structure of land tenure regimes
10. Misaligned incentives
11. Corruption & security

Which barriers are biggest for the poorest quintile of farmers in a context you know well?



System of Rice Intensification (SRI)

SRI: A Pro-Poor Technology?



India's rice revolution

In a village in India's poorest state, Bihar, farmers are growing world record amounts of rice - with no GM, and no herbicide. Is this one solution to world food shortages?



“SRI is set to change the face of paddy cultivation in the state as hundreds of thousands of small and marginal farmers have been adopting it following encouraging results” ~ Alok Kumar Sinha, Bihar Ag Production Commissioner (as quoted in state newspaper ‘Business Standard’ in 2013).

“Farmers who adopt SRI will not be affected by drought because it uses less water.” ~A.K. Sinha, Principal Secretary of Agriculture as Quoted in Times of India in 2011

SRI Study Findings

❖ Despite potential benefits of SRI to the poorest farmers, survey data from Bihar, India suggests that poorest farmers are the least likely to adopt SRI.

→ Only 10% of farmers in poorest quintile among SRI users

❖ Why:

- i. Lack of water availability and control
- ii. Design of subsidy program
- iii. Ineffective extension services

Technology Socio-technical Causal Mechanisms	Solar Irrigation Pumps	System of Rice Intensification	Drip Irrigation	Electric Motor Pumps	Rubber- <i>Walla</i> Pipes	Improved Seeds Varieties
(STCM)	(SIP)	(SRI)	(MIS)	(EMP)	(RWP)	(ISV)
Lack of financial assets	High	Low	Medium	Medium	Low	Low
Inappropriate technology design	Medium	Low	High	Low	Low	Low
Missing market linkages	Low	Low	Medium	Low	Low	Low
Lack of access to credit	High	Low	Medium	Medium	Low	Low
Missing Infrastructure	Medium	High	High	High	Medium	Medium
Ineffective extension services	Medium	High	Medium	Low	Low	Low
Lack of individual farmer capacity	Medium	Medium	Medium	Low	Low	Low
Weak capacity for collective action	Medium	Medium	Low	Medium	Low	Low
Structure of land tenure regimes	Medium	Medium	Medium	Medium	Low	Medium
Misaligned incentives	High	High	High	Medium	Low	Medium
Corruption & security	High	Low	Low	Medium	Low	Low

Ranked Barriers for Poorest Farmers in Bihar, India

STCM	Raw Score	Weighted Score
Missing infrastructure	21	2.3
Misaligned incentives	19	2.1
Structure of land tenure regimes	10	1.1
Lack of financial assets	9	1
Lack of access to credit	9	1
Ineffective extension services	9	1
Corruption & security	7	0.8
Inappropriate technology design	7	0.8
Lack of individual farmer capacity	6	0.7
Weak capacity for collective action	6	0.7
Missing market linkages	2	0.2



Bottom Line

1. Understanding which barriers impact the poorest farmers is an empirical questions
2. Whether the poorest farmers benefit from technology is almost always impacted by three attributes of the technology
 - i. The physical design of the technology
 - ii. The laws, regulations and incentives or managerial practices around the technology
 - iii. The availability of infrastructure and complementary technologies to the poorest farmers

Thank you



Rubber Pipes



Improved Seeds



Electric Pump Sets



System of Rice Intensification



Drip Irrigation



Solar Powered Irrigation Pumps